A Study on Application of Machine Learning in Course Stability Analysis

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A Study on Application of Machine Learning in Course Stability Analysis

針路安定性解析における機械学習の応用に関する研究

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1. Introduction

1.1 Energy consumption

1.1.1 Worldwide energy consumption

Energy consumption has rapidly increased since the 1950s. The significant increase in population and economic growth accompanied by technological development has led to an increase in energy consumption worldwide. As we can see from the Fig.1.1, the main source of this energy is fossil fuels such as oil and coal, which are feared to be depleted in the near future. Besides, the world total consumption was increased from 4,660 Mtoe (Tonne of Oil Equivalent) in 1973 to 9,938 Mtoe in 2018, where the consumption of fossil fuels is expected to increase with the future economic development of emerging countries, even if it is limited.

In addition, in the past 45 years, it is remarkably see that the share of demand for electricity has nearly doubled while Fig.1.2 shows upward trend in both the worldwide electricity's import and export in the last 2 decades.

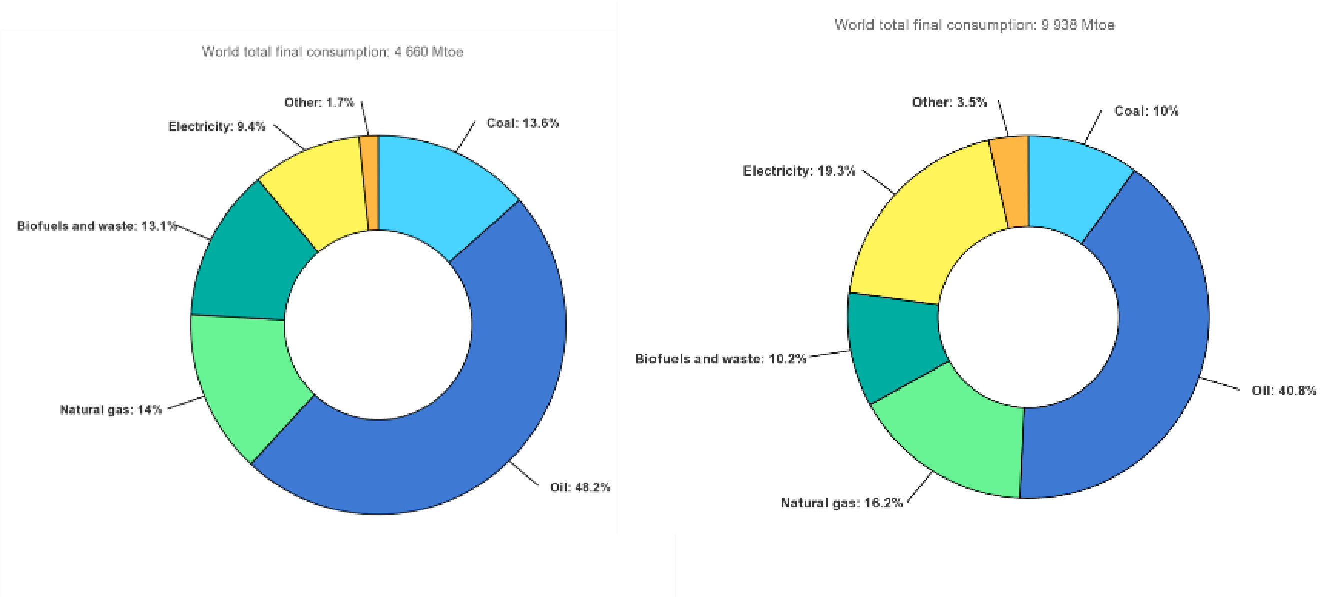

Fig. 1.1 Global share of total final consumption by source (1973,2018) [1]

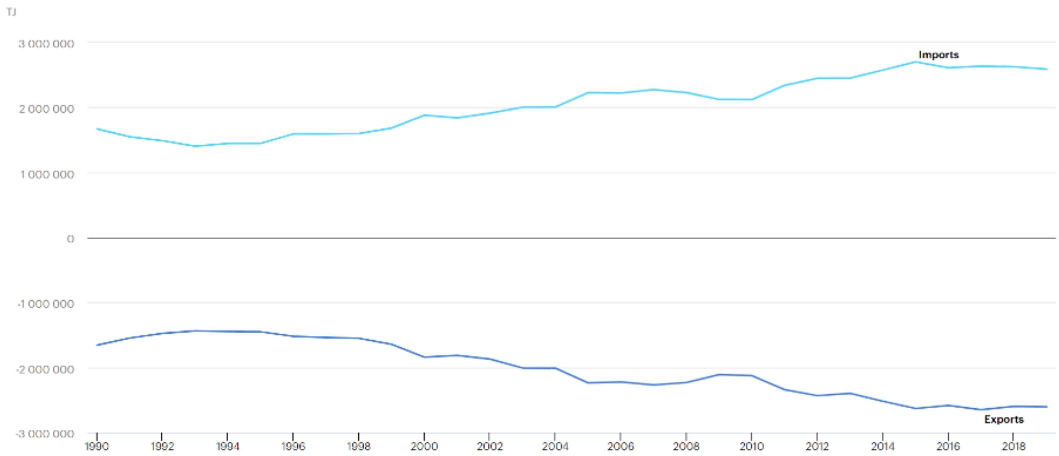

Fig. 1.2 Worldwide electricity imports vs. exports, World 1990-2019 [1]

Since the use of renewable energy rather than fossil fuel can be used permanently and reduce green-house gas emission, it is important to make it a main electric power sources in the world for addressing the growing demand for electricity and the strategy goal for sustainable development.

1.1.2 Energy self-sufficiency

Energy such as electricity, gas and petrol, being indispensable for human life, is supporting our society. In contrast to the world where energy is in great demand, Japan, as a country that lacks resources such as oil, coal natural gas and needs various measures to secure a stable supply of energy in Fig.1.3.

The energy self-efficiency ratio of Japan in 2017 was 9.6%, which is a super low level when compared with other OECD countries[2]. Overall, in the past 8 years even showed a declining rate although it has been increasing since 2014 when it was 6.4%, the lowest ever. A low energy self-sufficiency ratio results in dependence on other countries for resources, which make a country susceptible to the effects of international situations.

However, according to the situation in Japan, an island nation with a vast exclusive economic zone that has a high potential for marine renewable energy, including wave power generation, tidal power generation, and ocean thermal. Many of these technologies are still in the research and development stage. Among them, offshore wind power seems to have a promising future, which has a relatively large track record overseas and can make use of onshore wind power technology.

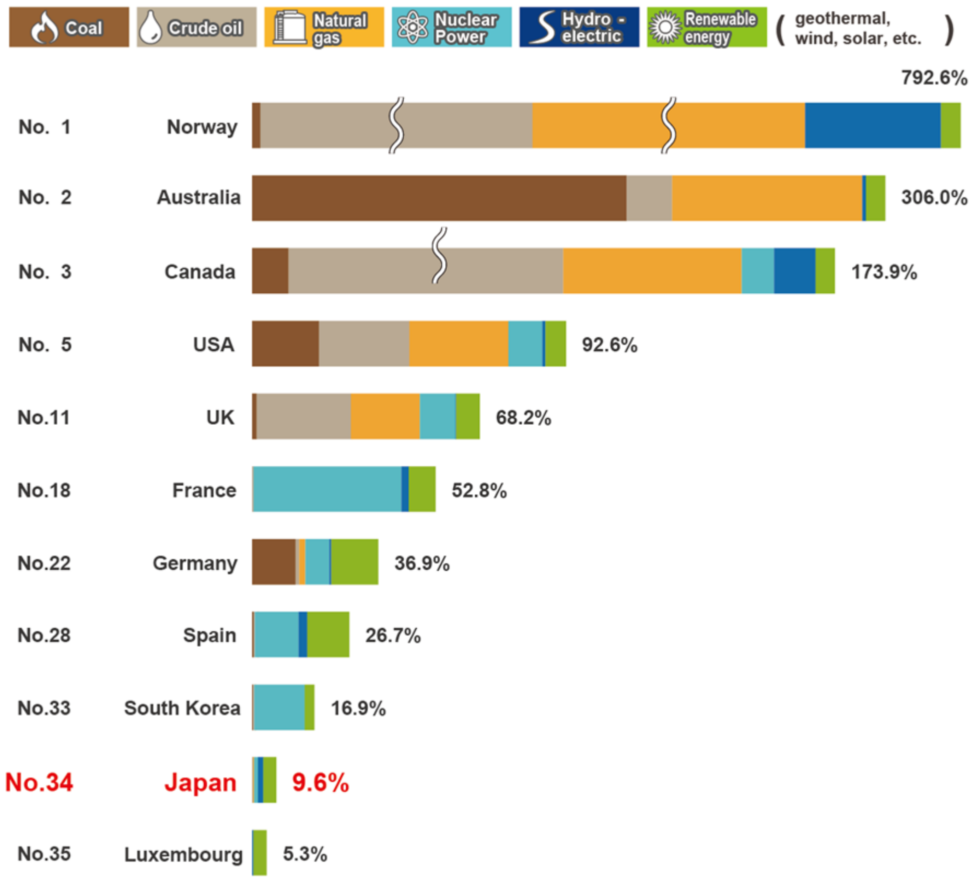

Fig. 1.3 Comparison of primary energy self-sufficiency ratios of major countries [2]

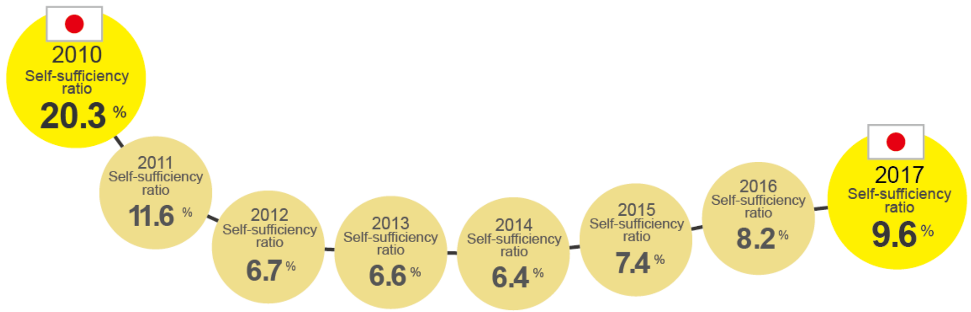

Fig. 1.4 Changes in Japan's energy self-sufficiency ratio from 2010 to 2017 [2]

1.2 Introduction of floating offshore wind power transmission

1.2.1 The previous wind power transmission

The current floating offshore power generation system commonly uses submarine transmission cables to transmit electricity from the power generation equipment to onshore by transmission lines from the floating structure to the seabed, seeing from Fig.1.5.

This power transmission method requires a special riser cable from the floating body to the seabed, and a laying ship is used to transport and install the submarine power cable from the seabed to the land. In addition, the strength of the riser cable is affected by large movements of the floating structure. The free-hanging method shown in Fig. 1.6, in which the riser cable is installed directly from the floating structure to the seabed, has limitations in mitigating the effects of the floating structure sway on the submarine transmission cable. Therefore, the lazy wave method shown in Fig.1.7, which has a connection point in the middle of the riser cable, are widely applied in oil drilling, etc.

However, there are still some difficulties that need to be addressed:

- interference by mooring cables, chains, etc
- floating body oscillation in regard to fatigue and bending stress absorption of riser cables in seawater
- Buckling of a riser cable at the seabed contact surface

To address the above issues that has needed a very high installation cost, which becomes one of the reasons for delaying the wind power generation. It is important to develop new types of transmission system for the purpose to significantly decrease the overall transmission cost including installation cost.

Fig. 1.5 Installation of submarine transmission cables for offshore wind power generation [3]

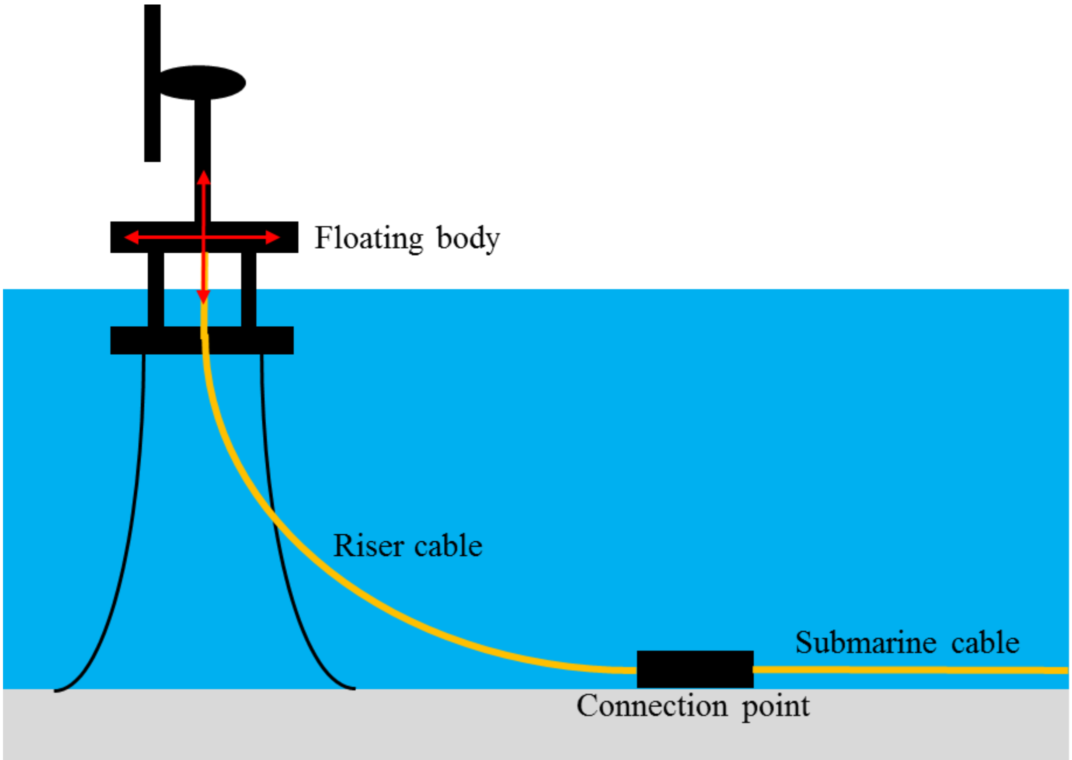

Fig. 1.6 Power transmission by free-hanging system[4]

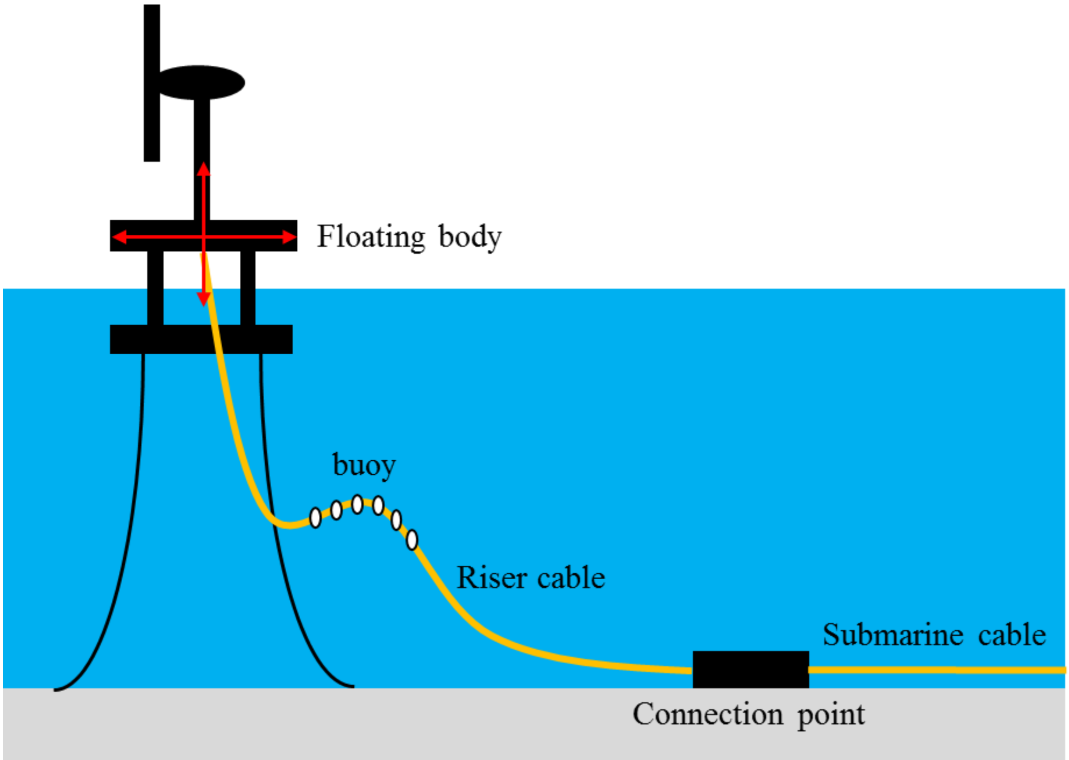

Fig. 1.7 Power transmission by Lazy Wave Method[4]

1.2.2 TLP type offshore tower

In the last few years, our research group proposed a new type wind power generation system[4][5][6],which could give a choice to replace the previous submarine transmission system and uses aerial power lines with offshore towers installed on a TLP-typed floating structure. There are several advantages compared with the previous wind power transmission system. It is expected to significantly reduce costs compared to conventional power transmission systems using submarine power cables. Furthermore, it is likely to be used not only for offshore wind power generation, but also a power transmission system between remote islands and offshore security systems. The offshore aerial power transmission system using a TLP-type offshore tower shows in Fig.1.8.

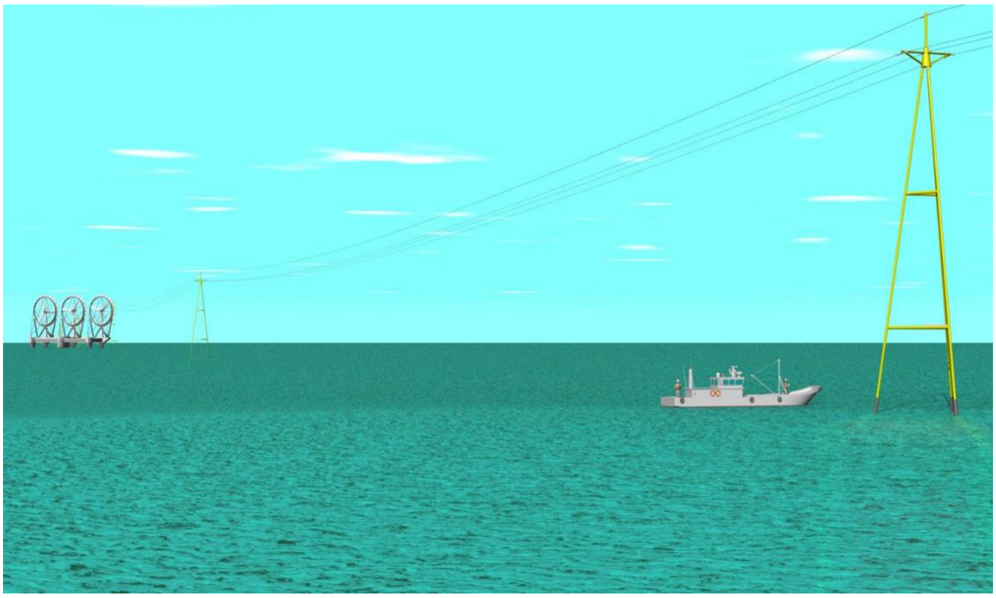

Fig. 1.8 Offshore airborne power transmission system using TLP-type offshore towers[4]

There are some advantages as follows:

- The installation method will be inexpensive and simple that only take a steel tower as loading device.
- It is easier to ensure the safety of the mooring cable since the penetrating part of the water surface is a thin member and the fluctuating external force caused by waves is small.
- Aerial transmission cables are lighter and less expensive than submarine transmission cables.
- Stress relief systems for cables due to floating motions may be easier to implement than in the sea.
- In the case of long-distance transmission, like shipping routes, a partial submarine power cable can be used to deal the problems without an intermediate buoy.
- It is easy to remove or replace the offshore towers.

However, floating body of the surface towing system is subjected to external forces such as currents and wind during towing and transportation, which may cause it to oscillate about its yaw direction. When the course stability of the system is maintained, the motion will gradually decay and disappear, otherwise, the oscillation remains, which may result in difficulty in maneuvering the towing vessel.

1.3 Motivation of this study

1.3.1 The importance of the ship towing system stability analysis

With progress in the development of deep-sea resources, high-efficiency applications of marine resources are also becoming increasingly significant. Power transmission system as a crucial part of the use of marine energy, instead of the conventional power system, the selection of the power transmission structure and to enhance the stability and economy of its structure are also tricky issues. Recently, Tension Leg Platform (TLP) is regarded as an offshore platform in a semi-submerged floating structure preserves many of the operational advantages of a fixed platform while reducing the cost of production in water and is connected to foundation pile driven into the seabed by a tendon, and moored using the tension force generated by the excess buoy. In this research, we focus on the new installation method, the surface towing system using small boats to take place the conventional installation method which using large construction vehicles with high cost. However, in the introduction of new installation method for overhead offshore wind power transmission, we need to improve the towing stability of the structure, mainly because towing operations without secured towing stability can lead to an unexpected planar motion of structures and marine accidents such as, encounter many dangerous situations that cannot imagine during towing and transporting. For example, the meteorological changeable sea area in Japan[7] and the Harbor Marine Traffic Guidelines with crowded sea traffic even the dangerous obstacles in the sea, stranding or collision with other ships or reef. If we can foresee the danger and avoid it in advance, it will not only ensure the stability of the navigation of the offshore structure, but greatly enhance the safety for both the staff and vessels as well as away from accidents.

To that end, machine learning is chosen as a helpful tool for learning and finally give a prediction of the swinging motion. Therefore, in my research I try to determine the course stability by machine learning method.

1.3.2 Application of machine learning in predictive model

Machine learning (ML) seeks to build intelligent systems or machines that can automatically learn and train them through experience, without being totally programmed or requiring any human intervention. ML offers smart solutions for organizations that want to implement processes that are just too complex to be manually set directly. Among these smart functions, ML is known for Predictive Modeling. In other words, we can predict the value of a dependent variable y by applying a hypothesis h on the independent variable x in Fig.1.9. Generally speaking, we use predictive modeling or predictive analytics in order to forecast future outcomes. For this purpose, we systematically collect data about an event and the data is also called historical data. After that, we train a statistical model. We use the trained statistical model to predict future results. Our aim is to use predictive analytics which can help us to understand possible future occurences by analyzing the past, that is to say, ML algorithms can learn from and make predictions on data, perform the data mining and statistical analysis, determining trends and patterns in data-driven decisions and to understand the data structure of the dataset and accommodate the data into machine learning models that could be applied to in my research.

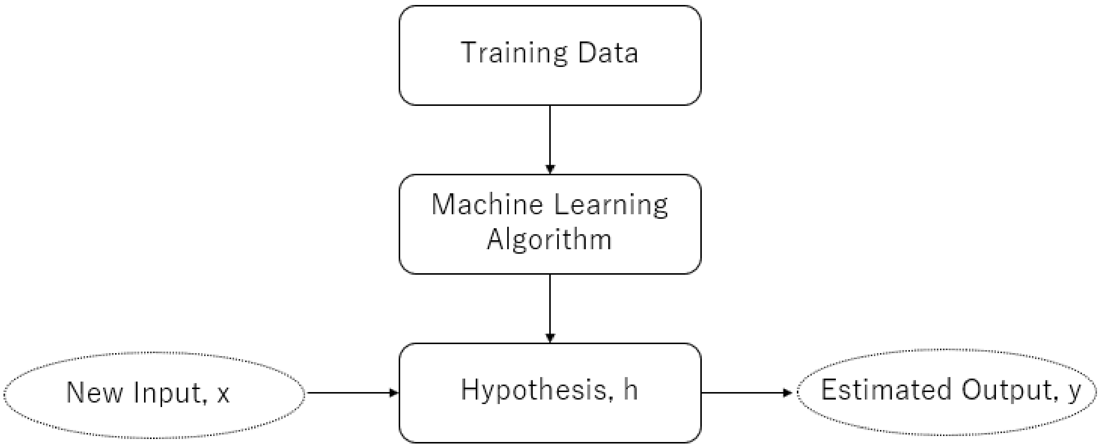

Fig. 1.9 The process of the machine learning in predictive model

There are some widely used predictive models as follow:

- Decision trees: decision trees are a simple, but powerful form of multiple variable analysis. They are produced by algorithms that identify various ways of splitting data into branch-like segments. Decision trees partition data into subsets based on categories of input variables, helping you to understand someone's path of decisions.
- Regression (linear and logistic): regression is one of the most popular methods in statistics. Regression analysis estimates relationships among variables, finding key patterns in large and diverse data sets, and how they relate to each other.
- Neural networks: patterned after the operation of neurons in the human brain, neural networks are a variety of deep learning technologies. They're typically used to solve complex pattern recognition problems and are incredibly useful for analyzing large data sets. They are great at handling nonlinear relationships in data and work well when certain variables are unknown.

In fact, Machine Learning offers several techniques that we can use to make predictions on the basis of historical data which are divided into several main types shown in Fig.1.10: supervised learning, unsupervised learning and reinforcement learning. Nonetheless, in the field of predictive modeling, there are both supervised learning techniques such as Linear Regression as well as unsupervised machine learning techniques that we can use for predicting the outcome.

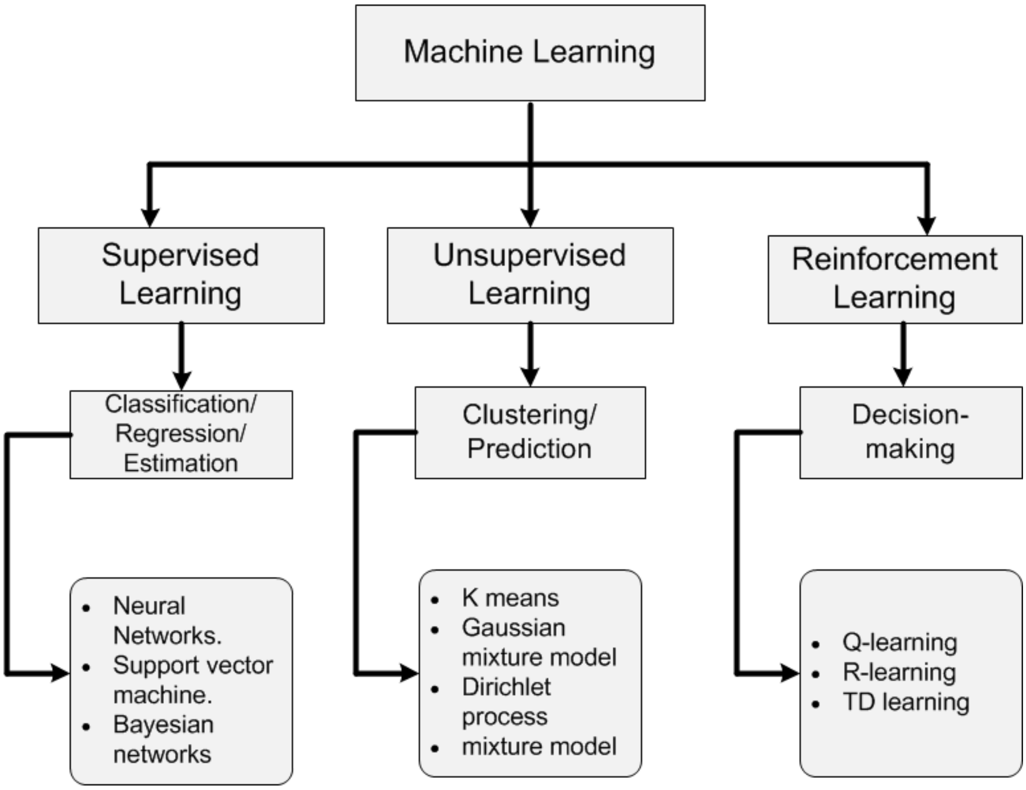

Fig. 1.10 Several main types of ML algorithms[8]

Compared with unsupervised learning, supervised learning shows the function to provides us with a powerful tool to classify and process data using machine language. With supervised learning we can use labeled data, which is a data set that has been classified, and to infer a learning algorithm. Furthermore, the datasets are trained with the training sets to build the machine learning model, and then will be label new observations from the testing set.

Among these learning methods, for my research topic, I choose neural networks for forecasting the stability of surface towing on triangle shaped bodies and using time-series analysis comprises the use of learning the pattern from a great deal of experiment data due to its good performance in predicting and performing tasks solely based on the learned pattern and forecast future conclusions on the basis of known past outcomes.

2. Research methods

2.1 Motion equation of towing ship system

Fig.2.1 shows the coordinate system of the towing vessel and the anchor. Consider the coordinate system O-XY fixed in space and the coordinate system G_1-x_1y_1, G_2-x_2y_2 fixed on the towing vessel and the anchor. The starting point of the towing cable in the system O-XY is (X_0, Y_0), and the coordinate system fixed on the towing vessel is (X_0, Y_0), The towing cable is represented by a single truss element connecting the two vessels and is connected to the vessel by a pin connection. The angle between the X-axis and the cable is θ_1, and its length is l_1. The azimuth of the towing vessel is φ_1 and the azimuth angle of the anchor is θ_2 and γ=θ_1- θ_2, σ = φ_1- θ_1.

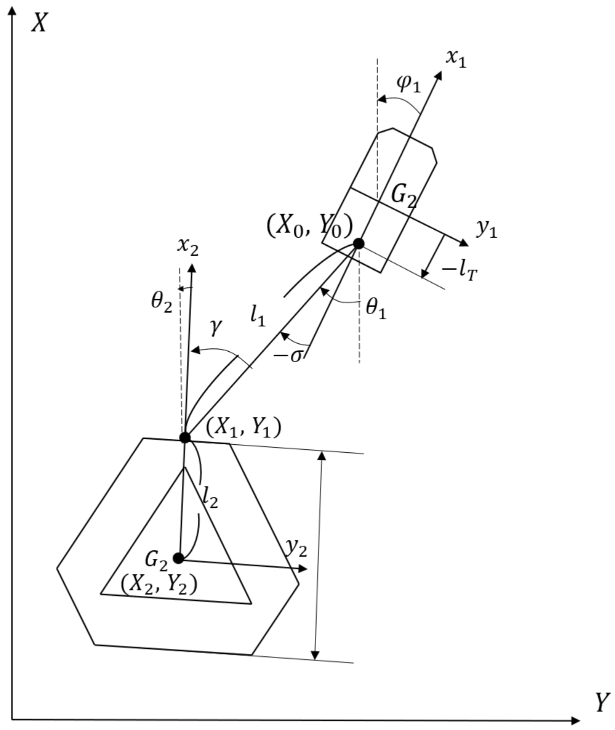

Fig. 2.1 Coordinate system of towing vessel and anchor [4]

In order to establish the mathematical model, the Lagrange's Equation is applied. In a physical system satisfies the requirement of a complete system that all generalized coordinates are independent of each other and at the situation of only consider the internal forces while the external forces can be ignored.

$$L = T - V \tag{1}$$

Where L is regarded as the Lagrangian Function, T is kinetic and V is potential energies.

For conservative systems, Lagrange's Equation is defined as follow:

$$\frac{d}{dt}\frac{\partial L}{\partial \dot{q}} - \frac{\partial L}{\partial q} = \tau \tag{2}$$

By calculation, the equation of motion of the towed vessel (anchor) is expressed as follow:

$$\begin{aligned}(m_2 + m_{y2})(-l_1\ddot{\theta}_1 - l_2\ddot{\theta}_2 + l_T\ddot{\varphi}_1 + \dot{v}_1) \\ &= -Y_{v2}l_1\dot{\theta}_1 + \left[-Y_{v2}l_2 + Y_{r2} + (m_{y2} - m_{x2})U\right]\dot{\theta}_2 \\ &+ \left[Y_{v2}l_T - (m_2 - m_{y2})U\right]\dot{\varphi}_1 - X_{uu2}\mathrm{U}^2(\theta_1 - \theta_2) \\ &+ Y_{v2}[v_1 + U(\varphi_1 - \theta_2)]\end{aligned} \tag{3}$$

$$\begin{aligned}(I_{z2} + J_{z2})\ddot{\theta}_2 &= -N_{v2}l_1\dot{\theta}_1 + (N_{r2} - N_{v2}l_2)\dot{\theta}_2 - N_{v2}l_T\dot{\varphi}_1 - l_2X_{uu2}\mathrm{U}^2(\theta_1 - \theta_2) \\ &+ N_{v2}[v_1 + U(\varphi_1 - \theta_2)]\end{aligned} \tag{4}$$

The equation of motion of the towing vessel (tugboat) is expressed as follow:

$$(m_1 + m_{y1})\dot{v}_1 + (m_1 + m_{x1})\,U\dot{\varphi}_1 = Y_{v1}v_1 + Y_{r1}\dot{\varphi}_1 + Y_\delta\delta + F_{Ty} \tag{5}$$

$$(I_{z1} + J_z)\ddot{\varphi}_1 = N_{v1}v_1 + N_{r1}\dot{\varphi}_1 + N_\delta + F_{Ty}l_T \tag{6}$$

Where, m_1 is the mass of the towing vessel, I_{z1} is the moment of inertia, m_{x1}, m_{y1}, J_z are the added mass and added moment of inertia. Y_{v1}, Y_{r1}, N_{v1}, N_{r1} are the linear manoeuvring by hydrodynamic differential coefficients. Y_δ, N_δ are the lateral force and turning moment generates by the steering, respectively, and δ is the steering angle, F_{Ty} is the lateral force component acting on the towing vessel due to the cable tension.

And the characteristic equation derived from the above is as follows:

$$D_4\lambda^4 + D_3\lambda^3 + D_2\lambda^2 D_1\lambda + D_0 = 0 \tag{7}$$

$$D_4 = l_1'(m_2' + m_{y2}')(I_{Z2}' + J_{Z2}') \tag{8}$$

$$D_3 = -l_1'\left[(m_2' + m_{y2}')N_{r2}' + (I_{Z2}' + J_{Z2}')Y_{V2}'\right] \tag{9}$$

$$D_2 = l_1'[(m_2' + m_{x2}' - Y_{r2}')N_{v2}' + Y_{v2}'N_{r2}'] - X_{uu2}'[l_2'(m_2' + m_{y2}')(l_1' + l_2') + I_{z2}' + J_{z2}'] \tag{10}$$

$$D_1 = X_{uu2}'[N_{v2}' + (l_1' + l_2')l_2'Y_{r2}' - l_2'(Y_{r2}' - m_{x2}' + m_{y2}' + N_{v2}')] - X_{uu2}'l_1'N_{v2}' \tag{11}$$

$$D_0 = [X_{uu2}' - (m_2' + m_{x2}')\ddot{X}_0'][l_2'Y_{r2}' - N_{v2}' - l_2'\ddot{X}_0'(m_2' + m_y')] \tag{12}$$

Therefore, the stable conditions for the towing vessel and anchor system as follows:

$$D_0, D_1, D_2, D_3, D_4 > 0 \tag{13}$$

$$D_5 \equiv D_3D_2D_1 - D_3^2D_0 - D_4D_1^2 > 0 \tag{14}$$

And the range corresponding to these conditions when the above characteristics equations are satisfied can be regarded as the stability region in analysis based on mathematical motion equation.

2.2 Summary of the previous experiment

Offshore power transmission has always been crucial in the development of marine energy. According to the previous research[3], Fig. 2.2, and Fig.2.3 show the stability test of the 1/30-scale anchor model in the circular flow tank, that is to say, the floating tower and anchor used for the course stability test in a circular flow tank in the Research Institute for Applied Mechanics, Kyushu University. In the previous experiments, in order to assess the towing operations, the towing stability of the towed vessel has been evaluated under different conditions, by moving the initial position away from the equilibrium position, the oscillating motion on the water surface was measured for observing the stability of the model.

First, the model was placed in the flowing water of a circular tank and the flow velocity and the length of the mooring connected to the model were changed as variables to measure the movement of the swaying motion. Next, at the same time, based on the swinging motion, the differential coefficient of maneuvering flow force is calculated appropriately using the least-squares method, which provides the theoretical foundation for the numerical analysis with mathematical model and used for setting a criteria for stable and unstable regions for the purpose of make a comparison of the experiment analysis result. Finally, the discussion is given in terms of both towing and course-stability of the towed vessel according to the experiment and simulation results.

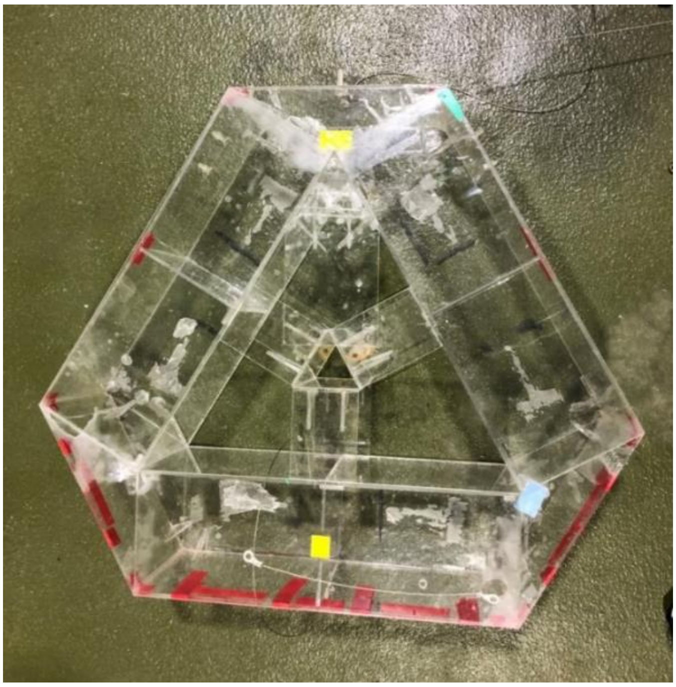

Fig. 2.2 1/30 Scale anchor

Fig. 2.3 Anchor in the circular flow tank experiment

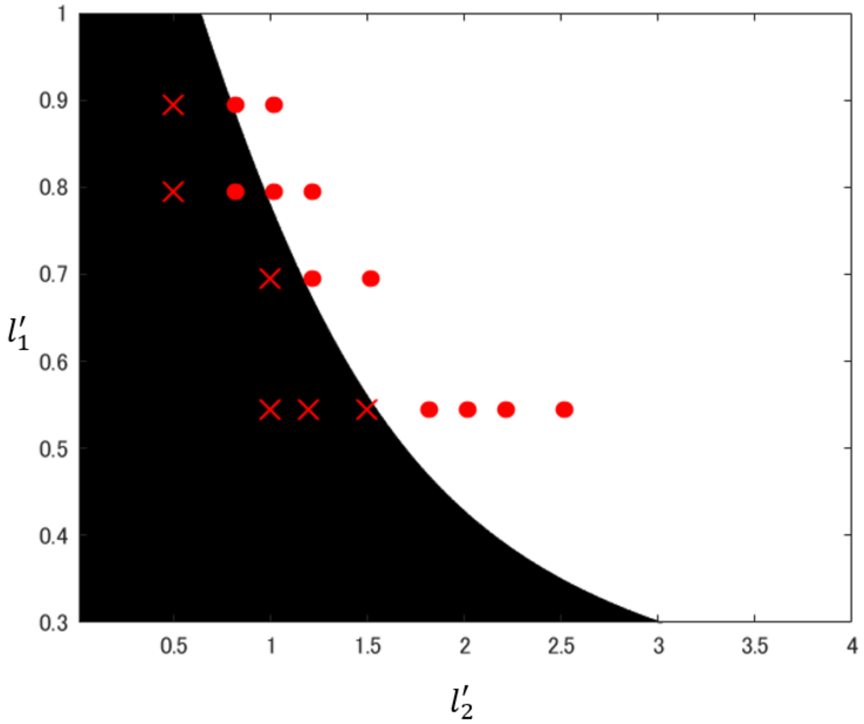

Fig. 2.4 Course stability evaluated by numerical and experimental result[4]

From the Fig.2.4, numerical results shows that the black area in the figure is the unstable region while the white area is the stable region. And the red • symbol in the Fig.2.4 indicates stable in the experiment, which can be regarded as the stability of the mooring system while the red × symbol indicates that the mooring was unstable in the experiment. The horizontal axis shows the non-dimensional value of the mooring length l_1' and the vertical axis is the non-dimensional value l_2'.

As shown in the figure below, we can see the towing system's stability areas was different under different velocity, especially it is confirmed to a strong correlation to the stability with the length of l_1' and l_2'. To put it in another way, we can get a conclusion that increasing the length of l_1' and l_2' is an efficient way to enhance the stability of the anchor, however, it may be dangerous when entering or leaving a narrow channel or port even it may strand or collision with other ships or reef.

Previous studies have been made in our research group on the towing operations, in which a towing stability experiment has been performed in circulating water tank and a numerical analysis has been carried out and compared to the experiment. Based on the previous analysis results, obtaining from the experiment and numerical analysis, it is not difficult to get the correlation between the length of l_1' and l_2' with the course stability judgement under different velocity, which also can get a similar conclusion with the two methods as explained, however, there are still some inconsistency parts that can not be ignored. More importantly, during the actual motion, due to effect of the external force or the accuracy of the experiment equipment, the theoretical results may not be guaranteed to be totally accurate and it is difficult to determine the parameters in the complex mathematical equations of the theoretical analysis.

Based on such a situation, in this research, in order to improve the accuracy and efficiency of the course stability analysis, machine learning is applied and the performance of neural networks algorithm is investigated

2.3 Predictive model of neural networks

Time-series forecasting is used to forecast the future based on historical observations[9] and there are many approaches to model time-series dependent on the theory or assumption about the relationship in the data. Traditional methods, such as time-series regression, exponential smoothing and autoregressive integrated moving average[10],are based on linear models. All these methods assume linear relationships among the past values of the forecast variable and therefore non-linear patterns cannot be captured by these models. One problem that makes developing and implementing this type of time-series model difficult is that the model must be specified and a probability distribution for data must be assumed. However, it is not easy to get a satisfied results in connecting approximating linear models with complex real-world problems.

For this reason, in the last several years, neural networks have been proposed as a promising alternative method for time-series forecasting. A large number of successful applications have shown that neural networks can be a very useful tool for time-series modeling and forecasting [11][12]. The reason is that the neural network is a universal function approximator which is capable of mapping any linear or non-linear functions, as well as it is almost like a data-driven method with few priori assumptions about underlying models but have the capability to identify the underlying functional relationship among the data.

The NN model consists of an input layer, an output layer, and one or more hidden layers built of processors called neurons, which are fully interconnected with neurons in the subsequent layer using adaptable weighted connections shown in Fig.2.5.

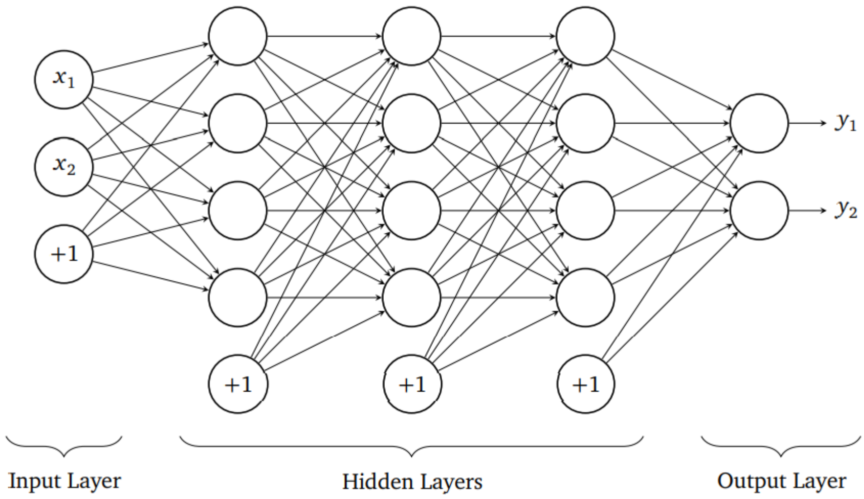

Fig. 2.5 Neural networks model[8]

Neural network that is used in understand different relationships with a given set of data to produce the best results from the changing inputs. At its core, a neural net evaluates a function f of the input $x = (x_1, \ldots, x_p)$ and weights $\omega = (\omega_1, \ldots, \omega_q)$ and returns output values $y = (y_1, \cdots, y_r)$:

$$f(x_1, \cdots, x_p, \omega_1, \cdots, \omega_q) = (y_1, \cdots, y_r) \tag{15}$$

That is to say, weights and biases (w,b) are the learnable parameters in the neural network model. In the NN, each neuron in a layer is connected to some or all of the neurons in the next layer. When the inputs are transmitted between neurons, the weights are applied to the inputs along with the bias, shown as:

$$Y = \sum (weight * input) + bias \tag{16}$$

It is like the black-box modeling tools which have the capacity to carry out non-linear mapping of an n-dimensional input space onto an n-dimensional output space, when the relations between the input and output spaces are unknown Neural networks are developed based on mathematical models. The choice of the NN model depends on the different setting of the system to be modeled. Considering that, on one hand, course stability analysis based on time series, and that, on the other hand, the NAR is a good predictor of the time series and it is used in this research study.

3. Establishment of the neural networks model

3.1 Nonlinear autoregressive (NAR) methodology

The nonlinear autoregressive (NAR) neural network represents a powerful class of models that has favorable qualities for recognizing time series patterns and nonlinear characteristics. In time series modeling, a nonlinear autoregressive model (NAR) is a nonlinear autoregressive model which is a standard instrument in linear black-box system identification[13] so that it is also regarded as a model used in extensive variety of nonlinear dynamic systems for time-series modeling. It has feedback connections which enclose several layers of the network. In order to obtain the full performances of the NAR neural network for course stability analysis prediction, it is necessary to utilize its memory ability using the past values of the predicted or true time series.

A standard approach for representation of a nonlinear plant in discrete time is to use a NAR model with inputs which relates the output y at the discrete time instant t to past outputs and inputs u. There are two different architectures of NAR neural network model in Fig.3.1, open-loop (also named series-parallel architecture) and close-loop (also named parallel architecture) given by the equation (17), (18) respectively:

$$\hat{y}(t+1) = F\begin{Bmatrix} y(t), y(t-1), \cdots, y(t-n_y), x(t+1), \\ u(t), u(t-1), \cdots, u(t-n_u) \end{Bmatrix} \tag{17}$$

$$\hat{y}(t+1) = F\begin{Bmatrix} \hat{y}(t), \hat{y}(t-1), \cdots, \hat{y}(t-n_y), x(t+1), \\ x(t), x(t-1), \cdots, x(t-n_x) \end{Bmatrix} \tag{18}$$

where, $F(\cdot)$ is the mapping function of the neural network, $\hat{y}(t+1)$ is the output of the NAR at the time t for the time $t+1$ (it is the predicted result of y for the time $t+1$) ; $\hat{y}(t), \hat{y}(t-1), \cdots, \hat{y}(t-n_y)$ are the past outputs of the NAR and at the same time, $y(t), y(t-1), \cdots, y(t-n_y)$ are the true past values of the time series, called also desired output values. $u(t), u(t-1), \cdots, u(t-n_u)$ are the inputs of the NAR. n_u is the number of the input delays and n_y is the number of output delays.

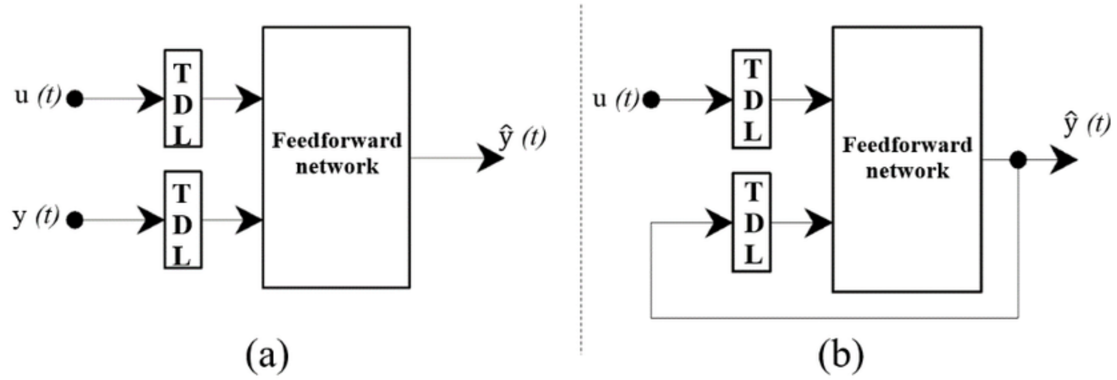

Fig. 3.1 Architectures of the NAR neural network

In the open-loop architecture, the prediction result of the time series $y(t-1)$ is obtained from the present and past value of $u(t)$ and the true past values of the time series $y(t)$ while in the close-loop architecture the prediction result is performed from both the present and past value of $u(t)$ and the past predicted values of the time series $\hat{y}(t)$.

As for this research study, during the training progress, close-loop architecture is used for making a comparison with the actual result due to the availability of the true past values of the time series. There are some advantages of using the close-loop architecture:

- In the situation of knowledge of the system's inputs and outputs is sufficient, training by the close-loop architecture could make a relationship with input values and values which provide a chance to derive the weights and biases and then to build the predictive model.
- Neural networks trained in close-loop more accurate and stable long-term predictions than the ones trained in open-loop [14][15].

During the training process, the usual training algorithms for Multi-Layer Perceptron (MLP) networks can be used. After the training phase, the NAR neural network is converted to the close-loop architecture which is beneficial for multi-step-ahead prediction.

The function $F(\cdot)$ is initially unknown as it is approximated during the training process of the prediction. In the NAR neural network model, the internal architecture that performs the approximation is the Multi-Layer Perceptron (MLP). The MLP offers a powerful structure used in the type of continuous nonlinear system.

As we can see from the Fig. 3.2, a classic MLP consists of three layers: input layer, hidden layer and output layer. The direction of the information flow throughout the layers is from input to output layer. In each layer, each neuron multiplies the input vector x_j given by the previous layer by the weights vector ω_{ij} to give the scalar product $x_j \times \omega_{ij}$ and then performed to obtain the following output shown as follow:

$$y_i = f(\sum_{j=1}^{n} x_j \cdot \omega_{ij}) \tag{19}$$

where i denotes the index of the neuron in the layer and j denotes the input index, f denotes the transfer function in the neural networks.

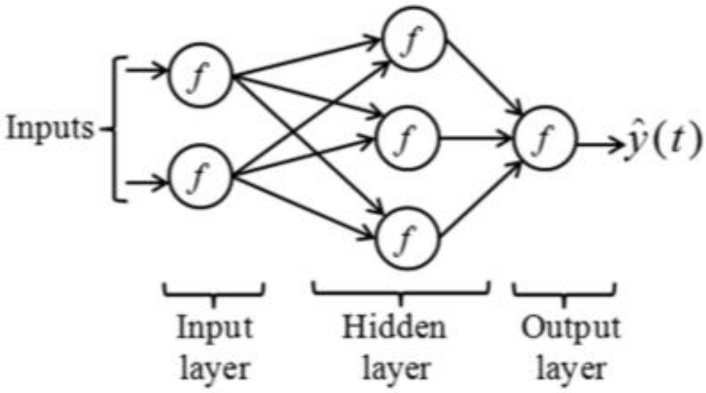

Fig.3.2 Details of a MLP network process[16]

3.2 Finite difference method

The controller proposed in this study is based on a discrete time-model neural network model that has been obtained by identification from existing input and output data is proposed.

I use the central difference formulas in the finite difference methods due to the fact that they yield better accuracy and the differential equation is enforced at the prepared input and output data, actually the trajectory of 2 types of angle in swing motion experiment.

The finite-difference methods (FDM) are a class of numerical techniques for solving differential equations by approximating derivatives with finite differences t, θ. In the finite difference method, the derivatives in the differential equation are approximated using the finite difference formulas. We can divide the interval of θ into n equal subintervals of time t as shown in the following Fig.3.3.

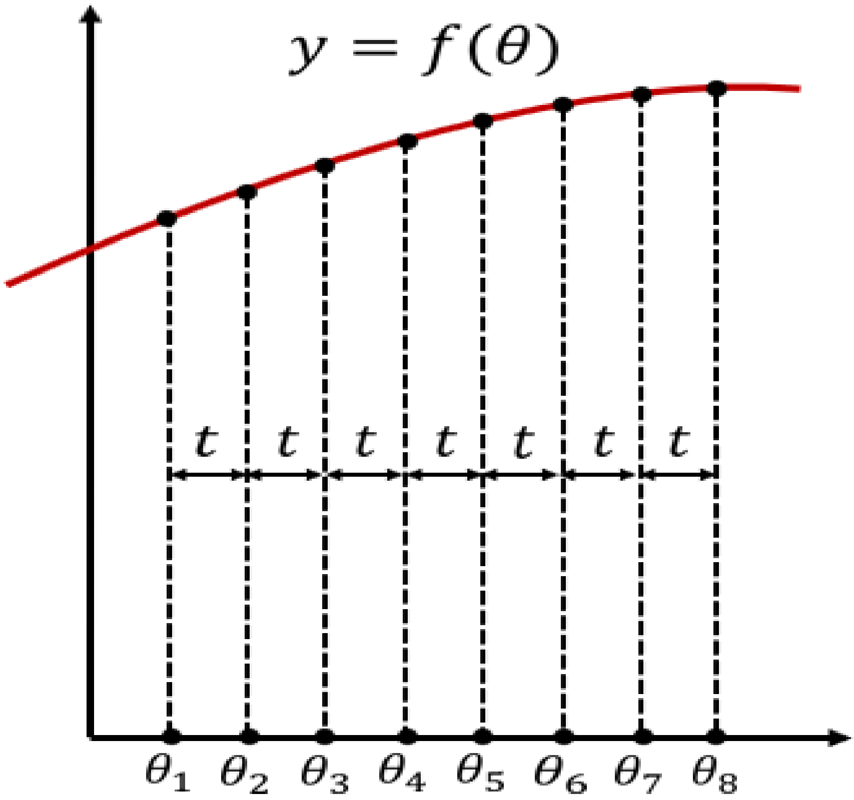

Fig.3.3 The finite difference method relies on discrete time-model

First, assuming the function whose derivatives are to be approximated is properly-behaved by Taylor's theorem, we can create a Taylor series expansion:

$$f(x+t) = f(x) + \frac{f'(x)}{1!}t + \frac{f''(x)}{2!}t^2 + \cdots + \frac{f^{(n)}(x)}{n!}t^n + R_n(x) \tag{20}$$

where $n!$ denotes the factorial of n, and $Rn(x)$ is a remainder term, denoting the difference between the Taylor polynomial of degree n and the original function. We will derive an approximation for the first derivative of the function 'f'by first truncating the Taylor polynomial:

$$f(x+t) = f(x) + f'(x)t + R_1(x) \tag{21}$$

Setting, $x=\theta$ we have:

$$f(\theta+t)=f(\theta)+f'(\theta)t+R_1(x) \tag{22}$$

Then assuming that $R_1(x)$ is sufficiently small, the approximation of the first derivative of $'f'$ is:

$$f'(\theta)=\frac{f(\theta+t)-f(\theta)}{t} \tag{23}$$

And the angle θ_n is in turn related to the angle of the next consecutive moment θ_{n+1} as follows:

$$f(\theta_{n+1})=f(\theta_n+t) \tag{24}$$

Thus, we can get the equation for the ω, denotes to angular velocity and a denotes to acceleration in this research as follows:

$$\omega=f'(\theta)=\frac{\theta_{n+1}-\theta_n}{t} \tag{25}$$

$$a=f''(\theta)=\frac{\omega_{n+1}-\omega_n}{t} \tag{26}$$

In this study, considering the effect of kinetic and potential energy on swing motion, through the prepared analytical sample available, the θ_1 and θ_2 that is used for deriving the primary and secondary functions ω, a by offline processing method. Therefore, in this study we can use 6 groups of data for input and 2 groups data for output training.

And the input and output values for offline processing shown as follows:

$$input:\begin{cases} l_1':\ the\ length\ of\ the\ towing\ line \\ l_2':distance\ from\ the\ center\ of\ gravity\ of\ the\ model\ to\ the\ towing\ point \\ \theta_1':the\ initial\ angle\ of\ \theta_1 \\ \theta_2':the\ initial\ angle\ of\ \theta_2 \\ U:\ flow\ speed\ in\ the\ circular\ water\ tank \end{cases}$$

$$output:\begin{cases}\theta_1: angle\ between\ towing\ line\ and\ x-axis\\ \theta_2: position\ angle\ of\ \ the\ anchor\\ \omega_1: first\ order\ derivative\ of\ \theta_1\\ \omega_2: first\ order\ derivative\ of\ \theta_2\\ a_1: second\ order\ derivative\ of\ \theta_1\\ a_2: second\ order\ derivative\ of\ \theta_2\end{cases}$$

3.3 Detailed description of NAR model setting steps

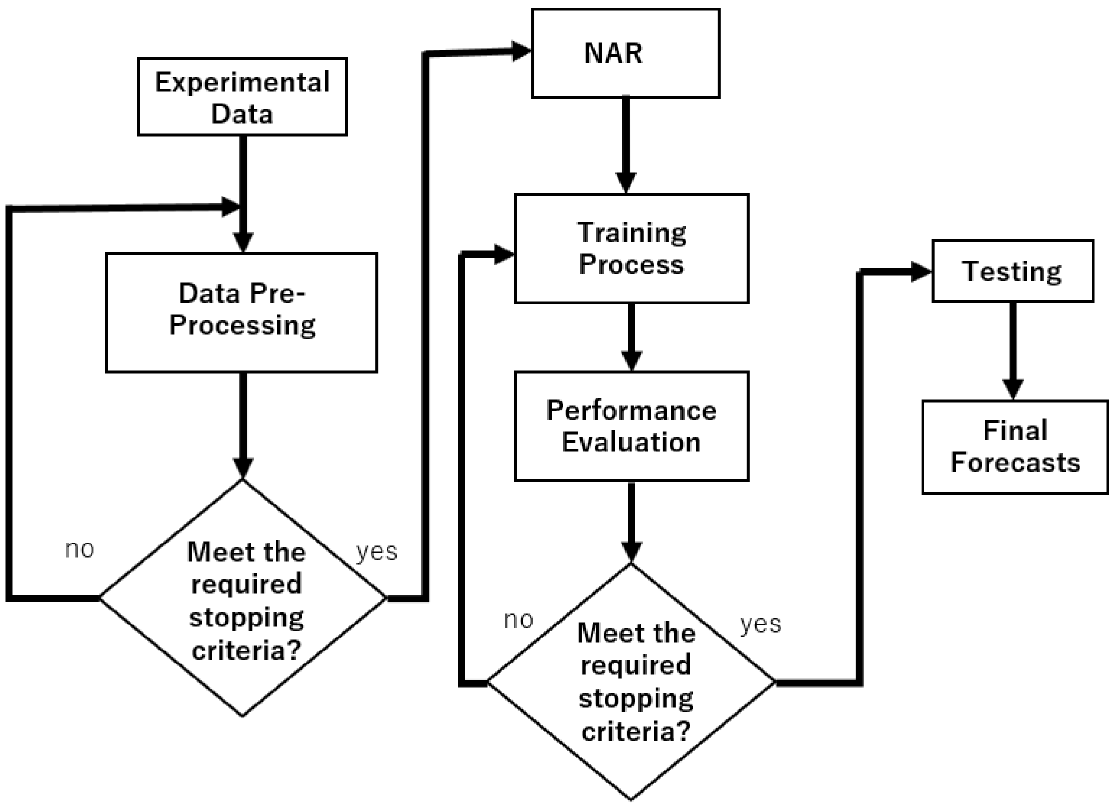

Fig.3.4 Flow chart of NAR model

In Fig.3.4, an approach based on NAR model to predict the stability of the ship towing system is developed.

The process is considered to select the database structure and the neural network configuration. Before starting test, the dataset is used to make the preparations of pre-processing, which can be used to model the NN and to be separated into three parts:

training, testing and validation sets. During the training process, the network's weights are optimized. The training procedure consists of 2 main steps: initialization and optimization[17]. In the initialization process, initial values are assigned to the weights and biases of the network randomly. The optimization process typically utilizes a gradient-based algorithm that is suitable for local search. During the training process, a specified number of inputs and their desired outputs are introduced in network and then the weights are tuned so that the neural network produces an output close to the target value. After finishing these processes, the validation set is used to simulate the model and evaluate its performance. Finally, Test step that makes the last evaluation on the model so that it is able to give a predictive result.

Table 3.1 Parameters of the NAR model structure

Property	Choice
Number of hidden layers	3
Number of hidden neurons	12 24 12
Delay number	1
Performance	Mean Squared Error
Training method	Levenberg-Marquardt

From the Table 3.1, this function is especially advantageous in the neural networks which are trained by back-propagation algorithms (Levenberg-Marquardt algorithm). For this time-series dataset, 70 percent of data are used for learning and 99.9 percent time-series lengths for prediction.

The steps of the establishment of the Narnet model are given as follows:

Step 1 Building system: the above-obtained network architecture is established and configure the input and output series from experiment data.

Step 2 Training and test: training is used to fit the model it means that the model must see and learn the historical data, the input and output data explained in the last section. The database is divided into 70% training data and 30% test data. The training and test data are selected randomly from the initial dataset.

Step 3 Training time series forecasting model: the aim is to fit the model using the training data. NAR model has been trained using Levenberg-Marquardt algorithm (LMA) as the training function and purlin as the transfer function for calculating layer's output from net input automatically.

Step 4 Validation is used to apply an evaluation of fitting the model when setting parameters, which is estimated by minimizing the error (MSE) between predicted and measured values. The goal is to adjust the parameters (weight and bias) to find a powerful model.

Step 5 The neural network is then trained based on the above data mentioned before in open loop, as a feedforward network.

Step 6 The trained neural network can be converted to close-loop mode and using closed loop design a is reformatted to simulate the network's closed loop response in order to carry out multi-step-ahead predictions.

Step 7 Finally, the test step that verify the accurate results that have been obtained, makes the last evaluation on the model and can be used to know if the networks have correctly learned the time dependencies of the experiment data.

4. Neural networks results of course stability analysis

4.1 Learning and prediction results of neural networks

As I mentioned in former chapter, for the purpose of evaluating the stability of the towing system, Stability analysis have been carried out based on motion equation and then validate the results through circulating water tank experiment under different conditions by our research group. According to the evaluation results, we propose a new method, combining the experiment data with neural network algorithms for the purpose to improve the accuracy and efficiency and to forecast the future trend of the ship towing system.

In this research, the proposed method is tested on the experiment data in time series. we choose 7 groups of data at each of the 3 different speeds as a learning set and to assess the performance of the prediction result.

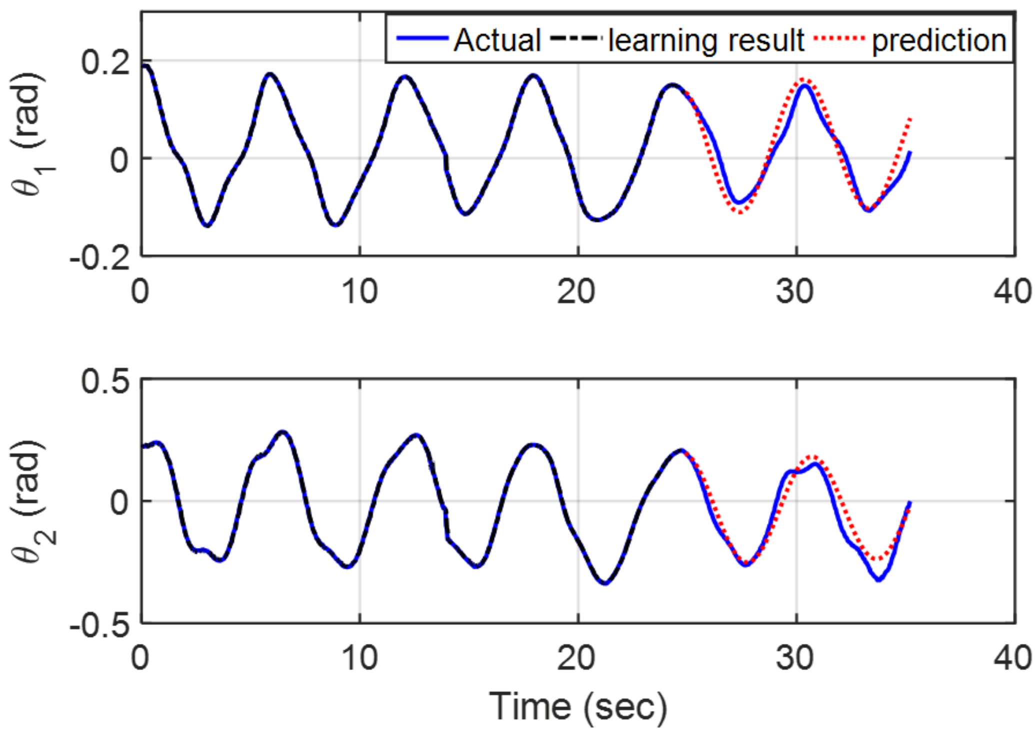

Fig. 4.1 Unstable example of comparison among neural network prediction result with actual and learning result

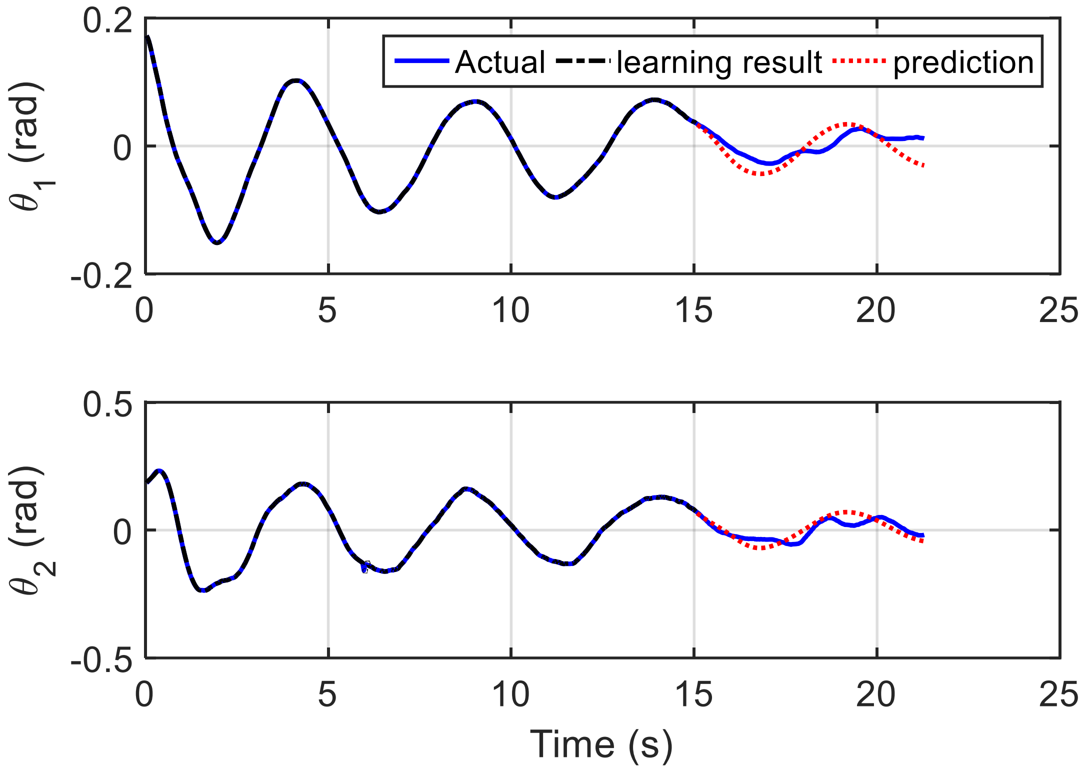

Fig. 4.2 Stable example of comparison among neural network prediction result with actual and learning result

As shown in the Fig.4.1 and Fig.4.2, there are 2 typical results in the unstable and stable state respectively through neural network algorithms, which includes of actual, learning and prediction result.

The solid blue line display illustrates the actual result, more clearly, the change of these 2 angle types of the ship towing system in the circular flow tank experiment measured by a video analysis software "Tracker". And the black dotted line illustrates the learning process which takes up 70 percent of the whole time series while the red dotted line illustrates the final prediction results for the course stability analysis which only take up the rest percentage of the time series, approximately 29.9 percent. Moreover, the horizontal coordinate is set to the measure time while the vertical coordinate shows the tendency of the angle: θ_1 (angle between towing line and x-axis) and θ_2 (position angle of the towed boat).

Furthermore, I establish a criterion judgement that taking into account both the method of predecessor and the actual situation, that is: oscillate about its yaw direction (moving from the initial position away to the equilibrium position on the water surface) tends to converge and the azimuth angle θ_2 of the anchor model within 3 degree is regarded as stable situation, otherwise is regarded as unstable situation.

However, from the Fig.4.1, it is hard to explain it whether stable or not clearly and the prediction result is hard to use as an independent judgement basis. In order to solve these problems, I make some improvements in neural network algorithms shown in the next section.

4.2 Course stability analysis results by neural networks algorithms

Table 4.1 Course stability analysis of neural networks algorithm results at $l_2' = 0.55$ in different velocities

	U=0.35m/s	U=0.45m/s	U=0.55m/s
$l_1' = 1.0$	Unstable	Stable	Stable
$l_1' = 1.2$	Unstable	Unstable	Stable
$l_1' = 1.5$	Unstable	Unstable	Stable
$l_1' = 1.8$	Unstable	Stable	Stable
$l_1' = 2.0$	Unstable	Unstable	Stable
$l_1' = 2.2$	Unstable	Stable	Stable
$l_1' = 2.5$	Unstable	Stable	Stable

From the Table 4.1, based on the 70% learning and 99.9% prediction process, we can get a conclusion about the judgement results of the course stability analysis based on the criterion explained as mentioned.

In general, flow speed in circular flow tank plays a crucial role of the stability of the ship towing system, to be more specific, lower speeds lead to ship towing system unstable, on the other hand, the system is able to maintain a stable state in the faster speed condition.

However, from the NNs results in U=0.45m/s, we cannot draw an apparent pattern whether there is a correlation between the length of towing line (l_1') with course stability under the same flow speed condition, which is inconsistent with the previous conclusion, that is, the course stability is inversely proportional to the length of towing line. In the next section, the cases of inconsistent judgment results by 2 different methods are discussed in detail and summarize the reason for these inconsistent results.

4.3 Compare with the previous analysis results

The following figures are the comparison between the previous analysis results (analysis based on motion equation results and experimental results) with the neural networks algorithm results in this research for judging the stability of the ship towing system.

To be more specific, the numerical results shows that the black area in the figure is the unstable region while the white area is the stable region. And all the red symbols in the figure are experimental results, the red • symbol shows stable in the experiment, which can be regarded as the stability of the mooring system while the red × symbol shows that the mooring was unstable in the experiment. Besides, all the blue symbols are neural networks algorithm results, the blue ○ symbol illustrates the prediction result of stability while the blue □ symbol illustrates the prediction result of unstable state. Furthermore, the horizontal axis shows the non-dimensional value of the mooring length l_1' and the vertical axis is the non-dimensional value l_2'.

The comparison of the conclusions obtained by these 3 approaches is divided into 3 groups at different flow speed shown as follows:

- U=0.35m/s:

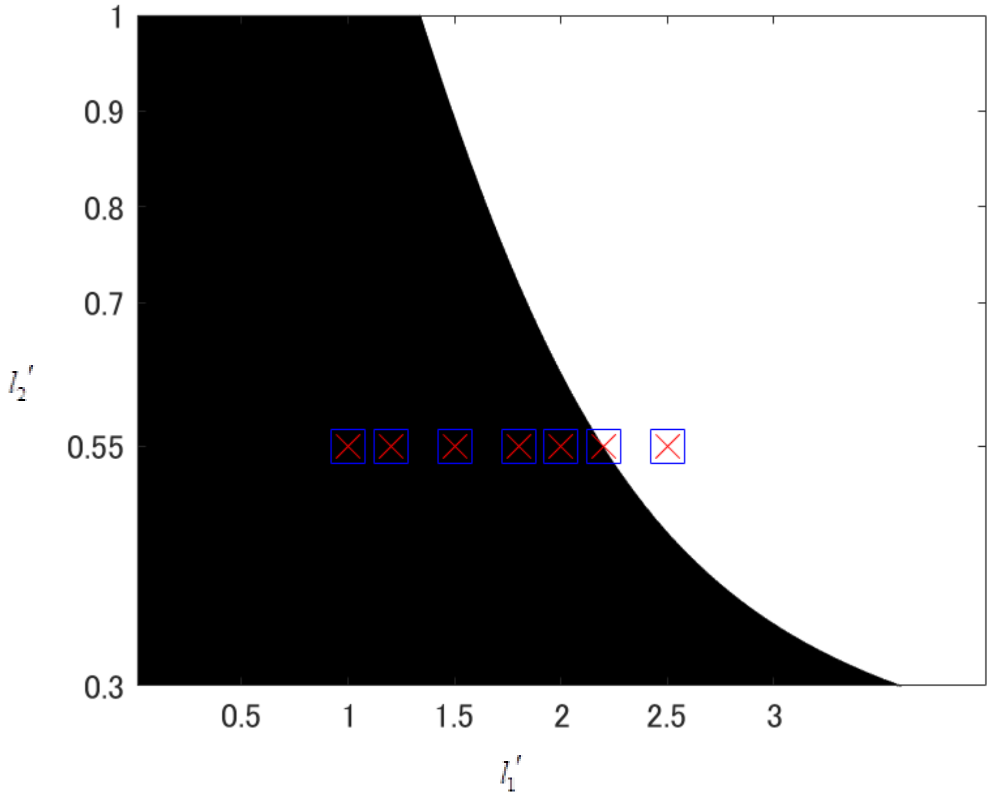

Fig. 4.3 Comparison between the previous analysis results and neural networks algorithm prediction results of course stability analysis at U = 0.35m/s

From the Fig. 4.3, we can get the conclusion when the flow speed equals to 0.35m/s in the circular flow tank, ship towing system tends to be unstable in all the various lengths of the towing line, which is concluded that the previous analysis results applied to the course stability are matched well with the neural networks predictive results. In another word, under lower flow speed condition, the ship towing system is confirmed to be in an unstable state.

In addition, according to the shortcoming mentioned in the last section, for the purpose of making a clear comparison with the actual experiment result and to judge the system more intuitively, I have made following improvements:

- Extend the model prediction time beginning from the initial moment, instead of only 29.9 percent for prediction time and add a 10 percent prediction after the actual swing motion.

- Make the stable region in the figure: the region within the black dotted line in the diagram is defined to be within 3 degree.
- Remove the presentation of neural networks learning result, so that more clear comparison conclusion between actual and prediction result can be obtained.

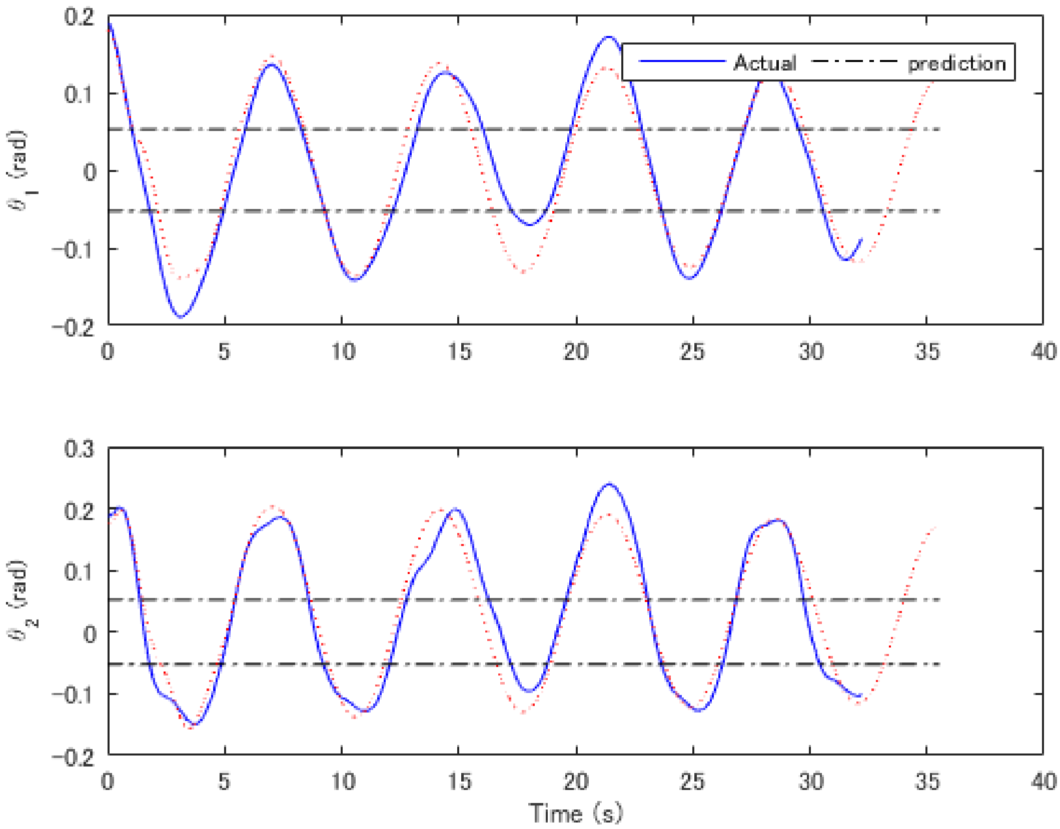

Fig. 4.4 Course stability analysis result at U=0.35m/s, $l_2' = 0.55$, $l_1' = 1.8$

From Fig.4.4, it is the prediction result of the θ_1 and θ_2 at U=0.35m/s, $l_2' = 0.55$, $l_1' = 1.8$, a typical unstable prediction result. During the whole course, there is no convergence trend in the change of the angle and even in the final prediction stage the angle is not within the stable range which is defined as within in 3 degree, in other words, the case in such condition leads to an unstable system.

- U=0.45m/s:

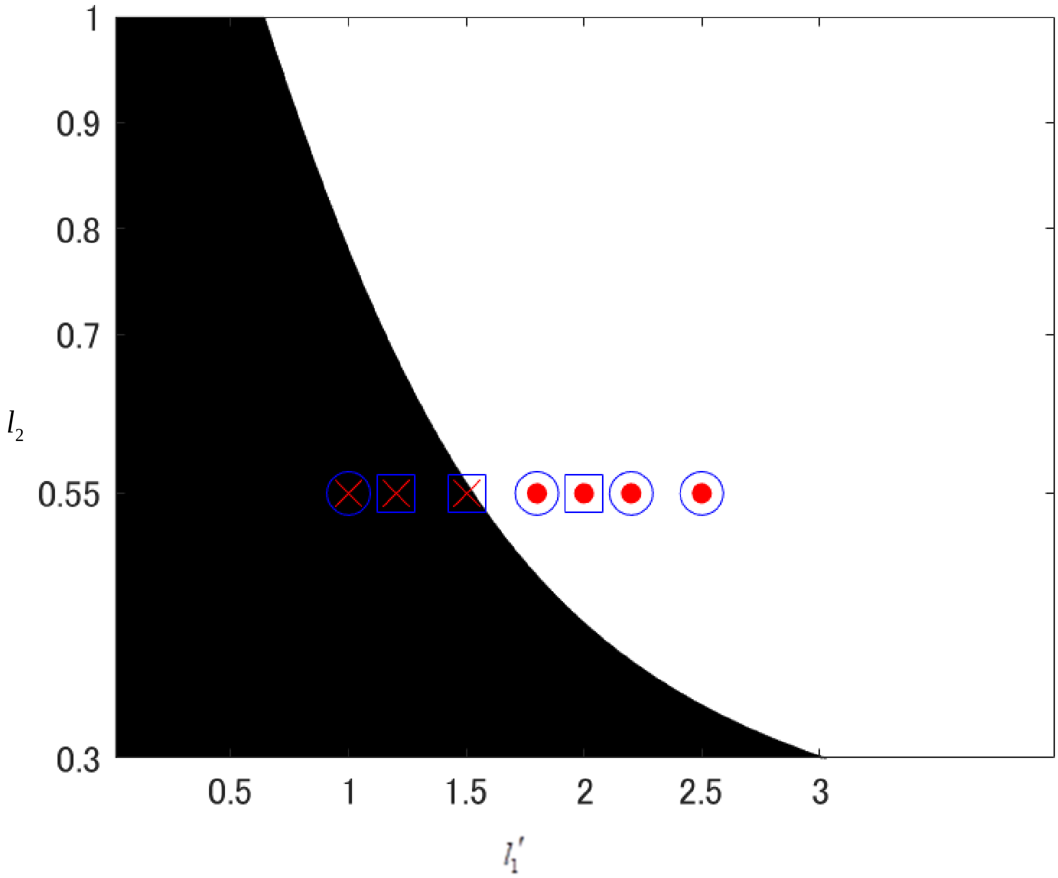

Fig. 4.5 Comparison between the previous analysis results and neural networks algorithm prediction result of course stability analysis at U = 0.45m/s

From the Fig.4.5, it is obvious that the different lengths of the towing line result in the different results of the stability judgment in the condition of U = 0.45m/s, to be more specific, the ship towing system with a longer towing line seems more likely to be stable in the experimental analysis results. However, seeing from the neural networks results, I find that longer length of towing line cannot be proven to be a more stable system under this flow speed condition. For instance, the system tends to be stable at $l_1' = 1$ while the system tends to be unstable at the $l_1' = 2.0$, and under these 2 cases, the analysis results are completely different compared to the previous experimental result for course stability analysis.

The following 2 cases are the examples of inconsistent judgment results:

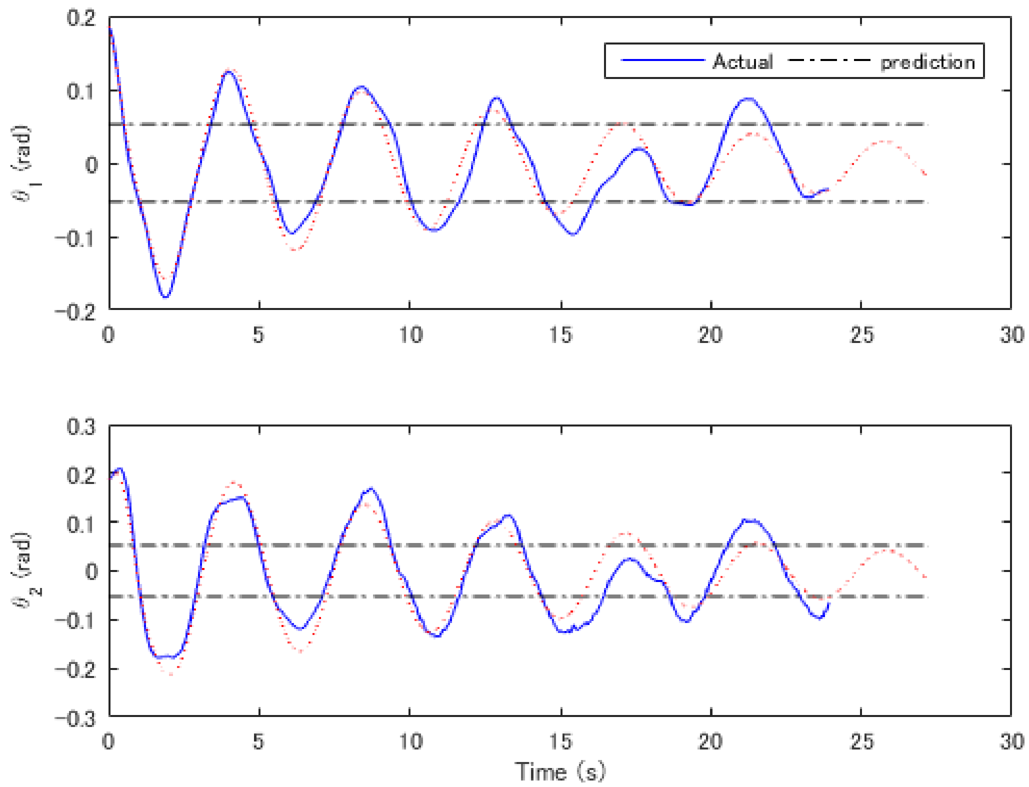

Fig. 4.6 Course stability analysis result at U=0.45m/s, $l_2{}' = 0.55$, $l_1{}' = 2.0$

From the Fig.4.6, the prediction result of the θ_1 and θ_2, using as a criterion of the course stability analysis, converged to within 3 degree in the final prediction stage, which is regarded as stable region and the case is also regard as a stable one in this research.

To put it in another way, if we make a comparison with other cases of proven stability, for example, like the case in Fig. 4.2, not only an obvious trend of convergence during the whole motion process can be seen easily, even the trajectory of movement within the last 5 seconds tends to be steady. By contrast, as the result in Fig. 4.6, coupled with the not clear convergence trend, the changes of angle become more intense than the previous movement may occur.

If we take the analysis into consideration, it seems that there are no fundamental differences in the judgment result between our neural network method and the former method.

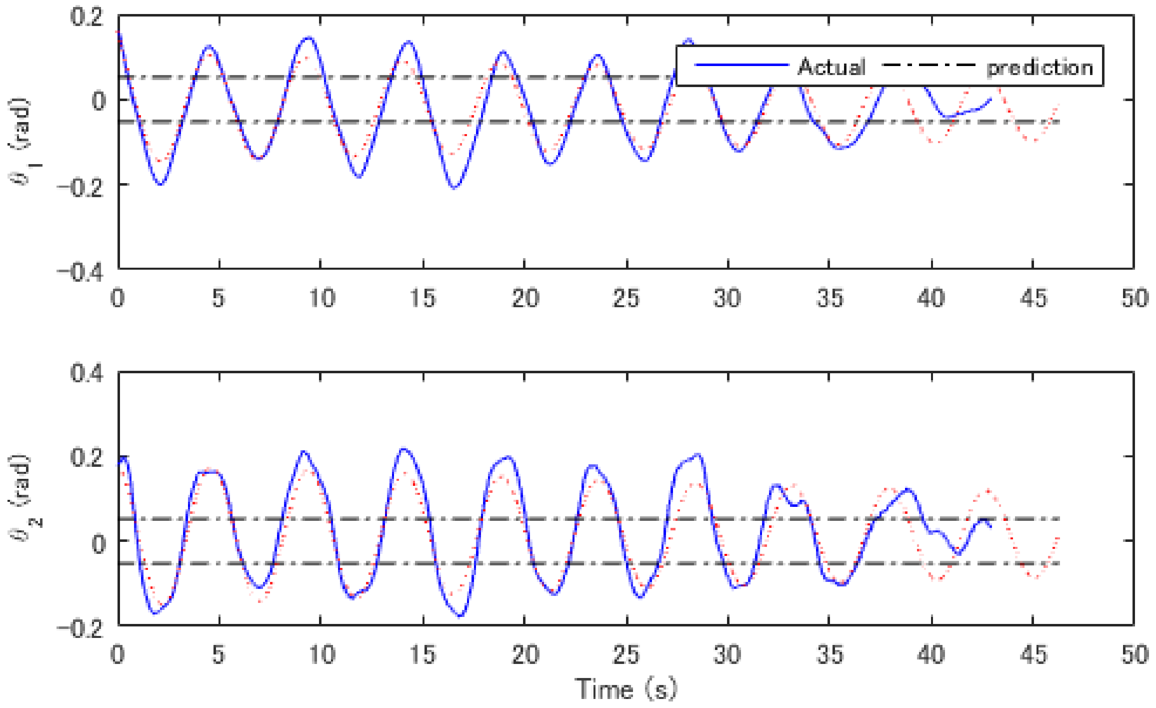

Fig. 4.7 Course stability analysis result at U=0.45m/s, $l_2' = 0.55$, $l_1' = 2.0$

From Fig.4.7, the prediction result of the θ_1 and θ_2, using as a criterion of the course stability analysis, not converging to within 3 degree in the final prediction stage, therefore, it is regarded as unstable case in this research while it is taken as a stable case in the previous analysis.

Obviously, compared with other cases mentioned before, the swing motion can be observed a higher frequency from the initial position to the equilibrium during the whole motion process under this condition, which can be taken as evidence of an extremely unstable ship towing system. On the other hand, there is a trend of convergence also can be seen during the whole process despite this. With this in mind, the current analysis results by neural network algorithms in this case are the judgment only based on the limitted data, that is to say, the conclusion may change if more data available.

- U=0.55m/s:

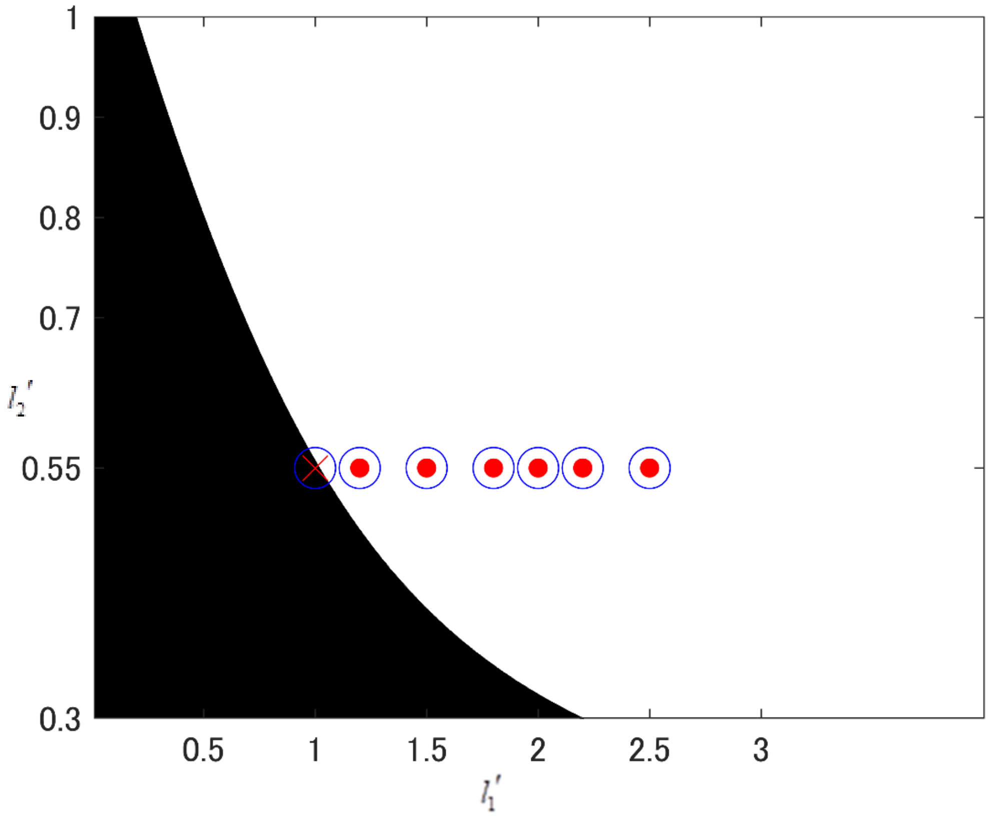

Fig. 4.8 Comparison between the previous analysis results and neural networks algorithm prediction result of course stability analysis at U = 0.55m/s

From the Fig.4.8, we can get the conclusion from neural networks algorithms when the flow speed equals to 0.55m/s in the circular flow tank, ship towing system tends to be stable in all the various lengths of the towing line and the conclusion is consistent with the previous inference that the ship towing system is more stable under faster flow speed condition while in the case of $l_1' = 1$, these two approaches yield inconsistent judgments about whether it is stable.

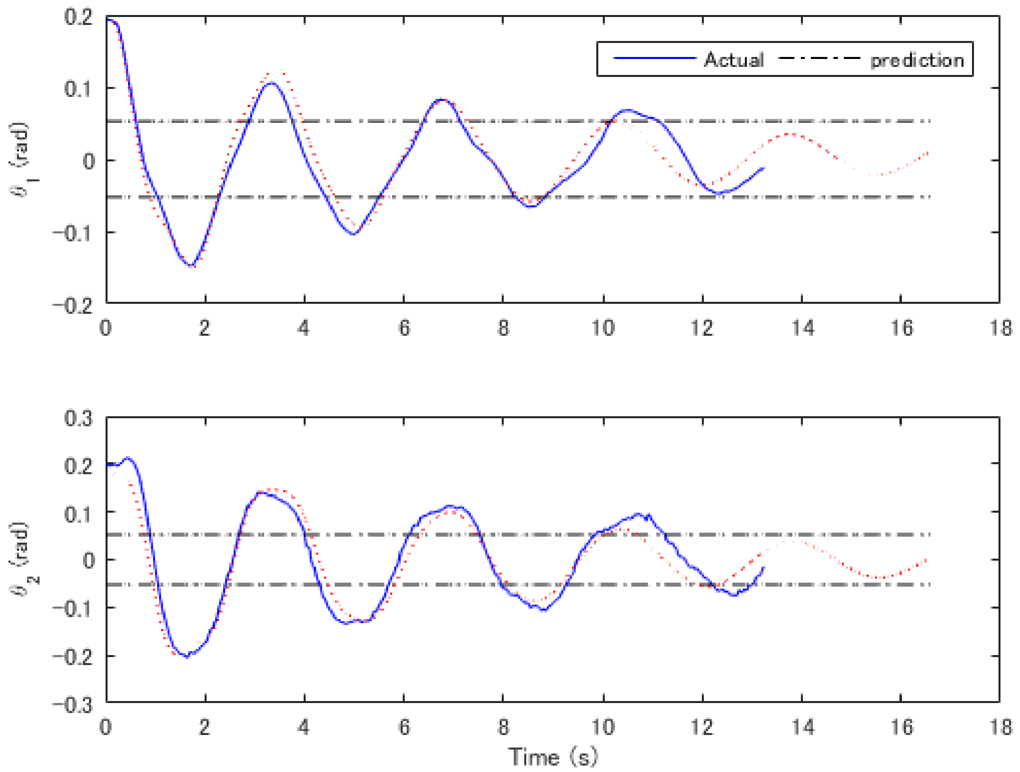

Fig.4.9 Course stability analysis result at U=0.55m/s, $l_2' = 0.55$, $l_1' = 1.0$

From Fig.4.9, it is the only case that shows an inconsistent result compared to experimental analysis result under the condition of flow speed equals to 0.55m/s in a circular flow tank.

According to the fundamental for stability judgment in this study, it is taken as a stable case as the angle converges to within 3 degree. However, like the case in Fig.4.6 (U=0.45m/s, l_2'=0.55, l_1'=2.0), we cannot obtain an obvious trend of convergence continuously in Fig.4.9 although it meets the criteria for judging stability due to the condition of limited experimental data available.

5. Conclusion and future prospects

In this study, we have provided a methodology to predict course stability in a set of experiment data using neural network algorithms, which can be regarded as a novel combination of machine learning and course stability analysis and fairly good prediction by the proposed method has been obtained. Having knowledge of relations between the input and output data in advance, and the features that explain these relations, could enable us to use these data as exogenous data for predicting.

In summary, we choose NAR neural networks algorithm as a helpful tool for solving the problem that theoretical analysis may occur inaccuracies and errors, more importantly, its good performance in predicting and performing tasks solely based on the learned pattern also can be used for forecasting the stability of surface towing system and using time-series approach to comprise the use basis of known past outcomes and learning pattern from a great deal of existing data to for effectively predicting future trend of the stability of the navigation of the offshore structures. Furthermore, when compared with the previous theoretical analysis, using neural networks algorithms give us a more convenient and efficient way for course stability analysis.

According to the analysis of results carried out in the previous section, considering those cases where there are prediction cases of stable and those where there are of instability. Thus, the first issue to be taken into consideration is flow speed in circular flow tank plays a crucial role of the stability of the ship towing system, that means lower speeds lead to ship towing system unstable, on the other hand, the system is able to maintain a stable state in the faster speed condition, which is concluded to be match with the former conclusion.

when it comes to the effect of the length of the towing line on the stability, as I mentioned before, although there are some inconsistent judgments compared to the previous analysis results, we include that the reason is due to insufficient data. For instance, in Fig.4.6 although the case meets all the requirements established in this study, it likely to be in an unstable state due to its trajectory not always in the trend of converge. And in Fig.4.7 although we take the case under such a condition as an unstable one, we can see the amplitude of the swing motion has a tendency decreasing. Based on these reasons, we summarize that the length of the towing line shows an inverse correlation, that is, the ship towing systems connected 2 floating bodies by a longer towing line is more likely to be in a stable state.

The analysis process using NAR model demonstrates that this network architecture is useful when experiment data is available and can provide suitable prediction accuracy, even give a choice to making a comparison with the theoretical analysis results. On the other hand, we also find that the insufficient data result in not precise enough prediction results.

In the future research, it should be targeted at developing more accurate and high-efficient predictive models connected with mathematical models and we believe stability prediction through machine learning will be applied in a wider range of fields.

There are some issues need to be improved as following:

- In the future research, if we can connect with a mathematical model of the ship towing system for making up for the shortage of not enough data available and increase the number of datasets by numerical simulation using the analytical method, it will greatly enhance the accuracy of predictive models.
- Improve the judgment method of stability or instability is of vital significance. For instance, besides the convergence angle within 3 degree, we should add more specific conditions for criterion of judging stability, for example, the convergence in a specified time,etc.
- In the experiment, the flow speed of 0.35,0.45,0.55m/s in the 1/30 scale model, however, in the actual system approximately equals to 2m/s-3m/s. Then, it will enhance the efficiency of the analysis results to study more flow speed cases such as 0.2,0.3.0.4m/s, which may get more patterns that match with the realistic situations.

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