MSE 2017 Project Individual Report

Optimization of Wave Energy Converter

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1. Introduction.

In 2015, Australia signed in The Paris Agreement, aims to limit the global warming blow the 2°C. According to the renewable energy target review report [2], this target will require major decarbonisation of electricity systems by 2050 to reduce the risk of dangerous climate change. The study, Energy in Australia 2015[3], demonstrates that during the 2013-2014 Australia used 248 terawatt hours of electricity, about 17 terawatt hours of this came from the large-scale renewable energy technology, this value achieved to the half of Australia's Renewable Energy Target [4], which is expected can achieve to 33 terawatt hours by 2020. To achieve the target of The Paris Agreement and contribute to the global environment, the Australia Climate Change Authority recently proposed that the Large-scale Renewable Energy Target (LRET) should be increased to 65% of electricity generation by 2050 [5]. This would require a rapid, large-scale transition to alternative emission-free energy systems.

In Australia, the wind and solar energy may dominate Australia's renewable energy competition, however, another competitor is hiding in the Australia's oceans. The study [1] demonstrates that Australia can have the largest wave energy resource in the World, which is about 1,800 terawatt hours, most of them come from the southern half of the continent which is between Geraldton and Brisbane. Compare to the wind and solar energy, the wave energy has some unique characteristics which provide an advantage beyond other renewable energy. For instance, Less variable and more predictable. It should notice that approximately 60% of the world's population lives within 60 kilometres of a coast, the distance between the wave energy sites and users is close, so it can minimise the transmission issues. Take a good use of wave energy can bring huge benefits to Australia and global environment.

However, the wave energy lacks exploitation, how to optimise the conversion of the wave energy became a hot aspect in the research area. The Ocean Wave Energy Research Group of Adelaide University had set up a Matlab model, which can simulate the process of the wave energy convert to the electric power [6] [7] [8]. The drawback of this model is the long run time, if it uses many coordinates of the buoys, the running time will be acceptable. As this reason, our project is to use the machine learning algorithms to train an accuracy model to take place the Matlab model and optimise the result. In addition, our project need to develop a web app, this app will let users who are interested in wave energy to do an experiment and compare the different machine learning algorithms.

2. Related Work

Predicting the power output of a renewable power is significantly important for the power industry. During recently decades, there were many studies on using machine learning algorithms to predict the different type of power.

The study [12] proposed a model which called auto-regressive integrated moving average (ARIMA) to predict the wind speed and wind power. A comparison between the ARIMA and Artificial Neural Network (ANN) for predicting the speed of wind is presented in the study [13] by Sfetsos. This study shows that the ARIMA model has a better performance than ANN model, however, when the number of train data was increased for ANN model, the accuracy of ANN model was improved. Multilayer Perceptron (MLP) model, which belong to ANN, was used to predict the wind power by the study [14]. This study shows that the MLP model had a better prediction in long-term power generation rather than short term. THERMO siphon solar heater is one device which can use solar energy to get hot water for human usage. Kalogirou et al. [15] used ANN to predict the performance of these devices. The performance was measured in terms of the useful energy extracted and of the stored water temperature rise. The ANN was trained using the performance data for four types of systems. The output of ANN is the useful energy extracted from the system and the water temperature rise. Seven input units, 24 hidden layers and 2 output layers comprise the network model.

There are three studies about the wave energy estimation. The study [16] based on based on Gaussian process regression Upper Confidence Bound with Pure Exploration algorithm (GPUCB-PE) to predict and optimise the wave energy output with 40 boys. The study [17] used eight different ordinal and nominal classifiers and one support vector regression algorithm to evaluate the wave energy estimation, this study mainly concerned wave height and energy flux prediction in a 6 h time-horizon. The study [18] used the data which comes from 22 sites in worldwide to predict the wave energy. As the data from the real world, the predict will be influenced by weather patterns and bathymetry and the prediction mainly determined by the probability distribution, if the distribution has heavy tails, the accuracy of the prediction will very low.

In conclusion, most of these previous studies are about wind energy and solar energy. There are a few studies about wave energy, so wave energy can be regarded as a new research area. Compare to previous studies, our machine learning model does not need to simulate the process of wave energy conversion to compute the power output and we do not concern the wave height. These works were done in Matlab model, the only work of our machine learning model is that according to the data which comes from the Matlab model to predict the wave energy.

3. Progress to date

Our project mainly contents two parts, one is the software development part, another is the research part. The target of this two part is to development a web application and to find a machine learning model to replace the Matlab model then optimise the result. This section will describe the current progress in both two parts.

(1) Software Part:

For a web application, the security is the significantly important requirement. As this reason, my first task for our web application is making sure our web application is stronger enough to defend the most attacks. I need make security strategies first and implement them in the backend of our web application. According to the requirements of our web application, I consider that the security of our web application should focus on three aspects: password security, session security and the SQL security.

1) Password security.

For a web application, a user account system is a necessary and basic requirement. The significantly important aspect of this system is the security of the users' password. In the development of the web application or website, the Hash algorithms usually are used to encrypt the passwords.

The Hash is a one-way function, it can convert any size of data to a fixed-length "fingerprint" which cannot be reversed. In addition, if the input data is changed a tiny bit, the result of the Hash algorithm is totally different. This feature makes Hash algorithm is very suitable for encrypting the password because we not only need to encrypt the password which cannot be decrypted but also needs to ensure that the correct verification of each user's password.

However, with the development of the hacking technology, there are many ways to decrypt the passwords. This report will discuss a little about these ways as following because only if we know how passwords are decrypted, we can effectively protect the passwords.

The easiest way to decrypt a hashed password is that to guess the every possible of a password and hashing all of them. When one of the guess's hash results is same with the hashed password, this means the password is decrypted successfully by a hacker. In general, Dictionary Attacks and Brute-force Attacks are the two common ways.

Lookup table is an extremely effective way to cracking many hashes of the same type very quickly. The core idea of this way is to pre-compute the hashes of the passwords in a password dictionary, then store them and their corresponding password in a lookup table data structure. A good implementation of a lookup table can process hundreds of hash lookups per second, even when they contain many billions of hashes.

Rainbow table is a trade-off technique between time and memory. It likes the lookup table, except that the speed of cracking is sacrificed to make the Lookup table occupies less space. Because it is smaller, more hash values can be stored in the same amount of space, so Rainbow becomes more effective.

To check the security level of some Hash algorithms which provide by PHP, I had done an experiment, the result is shown in Figure 1("√" means passwords are decrypted, "×" means passwords are not decrypted). For this experiment, I use the "a1696585" as the source password and use MD5, SHA1 and SHA256 to encrypt this password. Then I use three different online Hash Cracker tools to hack the encrypted password, the password was decrypted in few seconds. It should note that these online tools are the free edition. So, its capacity is limited, Nevertheless, these tools can decrypt the password, it means that directly use these Hash algorithms is extremely unsafety.

Figure 1. Online Hash Cracker

	MD5	SHA1	SHA256
hashkiller.co.uk	√	√	×
OnlineHashCrack	√	√	√
GPUHASH.me	√	√	√

In general, to protect the passwords a random string which called a "salt" can be appended or prepended to the password before hashing. With different salts, the same passwords are hashed into the completely different strings. The Cryptographically Secure Pseudo-Random Number Generator (CSPRNG) can help us generate the random salts. The CSPRNG is very different with the ordinary pseudo-random number generator because it is specially designed for encryption, which provides highly random and unpredictable random numbers. For the security of the passwords, the salts obviously should not be guessed by hackers, so the CSPRNG is a good method for our project.

Adding salt can prevent hackers from using specific Lookup tables and rainbow tables to quickly crack a large number of hash values, but it cannot prevent hackers from using Dictionary attacks or Brute-force attacks. High-end video card (GPU) and customised hardware can help hackers to hash billions of times per second, so this kind of attack is still very efficient. To reduce the efficiency of hackers, we can use a technique which called key stretching. The core idea of this technique is that making the hash function very slow, even if hackers have the hyper-performance GPUs or custom hardware, the speed of Dictionary Attack and Brute-force attack is still too slow and unacceptable for them. The final goal of this technology is to slow the speed of the hash function to impede the hackers, but the caused delay cannot be noticed by users.

The implement of the key stretching technique bases on the special CPU-intensive hash function. The PHP provides a key stretching technique which called PBKDF2. It uses the number of the iteration as a parameter, this value determines how slow the hash function will be. For our project, we can run a performance benchmark and find the value of iteration number which makes hash function consumes about 0.5 seconds. In this way, our project can be as secure as possible without impacting the user experience.

2) Session Security.

For Web applications, the first principle of security is that don't trust the data from the client, make sure the data is validated and filtered, then the data can be used in the application. However, because of the stateless nature of HTTP, in order to maintain the state between different requests from the same user, the client must send a unique identity identifier (session ID) to indicate its identity. Although this is contrary to the security principle, to maintain the state make us do not have other choices. This also leads session to became a very fragile link in the Web application. Because the PHP built-in session management mechanism does not provide security handling, we need to establish appropriate security mechanisms to guard against session attacks. The Session hijacking is a mainly way to attack. According to the features of the Session hijacking, I use serval ways to defend as the following:

a. Update the sessionId. The new sessionId will be generated when each page reloads. Using this function can effectively prevent the Session hijacking.

b. Set HttpOnly. In general, the session saved in the cookie on the client side. Cookie has an attribute which called HttpOnly when the value of it set as true, it will prevent client script from accessing this cookie, thus effectively prevents XSS attacks.

c. User-Agent. The user agent is used to check the consistency of the requests. The different browser has different user agent, if we sever find one user always use the Chrome to browse the internet, but suddenly after check the user agent we sever find this user's browsing change to IE, this means probably one session hijacking is happening. Let the user input the password is a good way, even if this is not a session hijacking, input the password will not influence user much.

3) SQL Security.

For our project, the mainly threaten for our database is the SQL injection. SQL injection has been regarded as the most serious threats for Web applications [9]. SQL injection refers to insert a SQL command into the inquiry string to spoof the server to execute a malicious SQL command. Specifically, it has the ability to inject (malicious) SQL commands into the backend database engine by using existing applications, through the SQL injection one attacker can gain complete access to the underlying databases. Because some important and sensitive information is always saved in the database, the resulting security violations can include identity theft, loss of confidential information, and fraud. The cause of the SQL injection is relatively simple and well understood: insufficient validation of user input.

To protect our project, currently, I use Input validation to protect our web application. Check the validity of the user input and make sure that the content of the input only contains legitimate data. Data checking should be executed on the both server and client side. The validation on the server side to compensate for the vulnerability of client-side validation mechanisms. On the client side, the attacker is likely to get the source code of the Web page, modify the validation legitimacy script (or delete the script directly), and then submit the illegal content to the server through the modified form. Therefore, the only way to ensure that whether the validation operation is actually executed or not is to execute validation on the server side. For the input validation, I had written a PHP function to filter the illegal input.

Although I had taken some measurement to keep our web application safety, it still has many places can be improved. The follow-up work will continue in the next semester if it needs. In addition, I also work on the notification function, our web application needs a notification function to notify the user when the result of the computation can be displayed in the web application. Because if users upload the big size of data, it needs some time to train the model. Normally, the web application can use the email to notify the users, this function will be implemented in next semester. This semester I want to find another is that use the Short Message Service (SMS) to notify the user. Currently, I use Java code to call the Amazon interface to implement it. After some tests, it can work now, but in the presentation, it did not work. I check the command line find that the cell phone number is wrong. In addition, this function is not integrated with our web server, because I think my implement is not very familiar, it needs the optimisation.

(2) Research Part

The target of the research part of our project is to find a machine learning model to replace the Matlab code. This model should, has the capacity of predicting the power output as accuracy as possible, at the same time, the running time should be short. We need to find more models and compare the performance of the model.

1) Benchmark

To measure the performance of the model, we use the Root Relative Squared Error (RRSE) as the benchmark. The formula of this function is as the following, which $\hat{\theta}$ means the prediction value, θ means actual value and $\bar{\theta}$ means the mean of the θ.

$$\mathrm{RRSE} = \frac{\sum_{i=1}^{N}(\hat{\theta}_i - \theta_i)}{\sum_{i=1}^{N}(\bar{\theta}_i - \theta_i)}$$

The reason why use RRSE is because it can tell us how much the result is different from its mean value, RRSE is very sensitive to the larger error of the test, it can well reflect the precision of the predict, so the value of the RRSE is the smaller the better. If the RRSE is low enough, that means the machine learning can replace the Matlab code.

2) Datasets

To introduce my task in the research part, I must introduce our datasets in advance. We had used 5 kinds of datasets:

The first dataset is that we use Matlab code to generate a dataset which contains 100000 data, the content of this dataset is the coordinates of the 4 buoys and the output power, in the following content we call this data as the Raw dataset.

The second dataset is what we mentioned in the project proposal [10], it contains 12 features from the coordinates of the 4 buoys, these features are extracted from the Raw dataset, in the following content we call this data as the Feature dataset.

The third dataset is called Raw dataset with High Precision. This dataset also comes from the Matlab code, the difference between it and the Raw dataset is that this dataset has a higher precision on output power.

The fourth dataset is called Sorted dataset. This kind of dataset is the dataset which after the Raw dataset or High Precision Original dataset is sorted. The way of sorting is divided into three ways, horizontal, vertical and toBase. For instance, we move the coordinate which closes to the Y axis the first buoy and we call this as the horizontal move.

The fifth dataset only contain the coordinates of the two buoys, and this dataset has a high precision output power and it is also sort as the horizontal, vertical and toBase.

In the following content, we will call it as the Sorted dataset of Two Buoys.

3) Research Progress.

I conclude my research work as four phases as the following, the first two phases are before the project proposal, so in this report, I will just simply introduce them, the details information can of these two phases be found in the project proposal [10].

a. Choose the machine learning tool and the algorithm.

According to the requirement of the web application, we need integrate different machine learning components to our web application, so each member of our group need to research one or two components or more components. There are some machine learning tools for us to use as a component of our application, such as Weka, LibSVM, scikit-learn etc. Weka is one open source tool which collects many machine algorithms, it either can work on Windows or Linux and it is easy to use, so I choose the Weka as the first machine learning tools.

The Weka is a mining big data tool which developed by the Machine Learning Group at the University of Waikato. It provides many Machine Leaning algorithms for different targets. So, the first I need to filter the algorithms. As I mentioned above, our target is to predict the value of wave power, so the algorithms which can predict the value are my target algorithms. I used the Raw dataset as the input data and used different machine learning algorithms to train and test the input data, the result is shown in Figure 4.

Figure 4. Different result with different machine learning algorithms

Algorithm Name	RRSE
Linear Regression	100%
ElasticNet	100%
Pace Regression	99.99%
Isotonic Regression	98.98
Multilayer Perceptron	82.13%

Our project need predict the wave power as accuracy as possible and stable, that means the RRSE of our machine learning model need as low as possible. The Figure 4 shows that compare to other algorithms, the Multilayer Perceptron has a better performance on the RRSE. So, I begin to focus on the Multilayer Perceptron and try to reduce the RRSE. The Multilayer Perceptron (MLP) is one kind of artificial neural network model, through one or multiple hidden layers it maps a set of input data onto a set of appropriate outputs. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neurone (or processing element) with a nonlinear activation function [11].

b. Extract features and adjust the parameters

Obviously, the RRSE in phase A is not acceptable for our project, then I try to find a way to reduce the RRSE. After discussing with the group members, we proposed a hypothesis, it is that through the extend more attributes the RRSE can be reduced.

The Raw dataset contents the coordinates of four buoys, according to the coordinates, many features can be calculated through the geometry, such as the distance between two buoys and the angle between each buoy and X- axis. Among all the features, 12 features were picked up and build up as a new data which is the Feature dataset [10], compared to the Raw dataset, it has four more attributes. Figure 5 shows the 12 features of four buoys.

Figure 5. 12 Features

(1) max distance between any two buoys
(2) min distance between any two buoys,
(3) average distance between any two buoys,
(4) max degree d between any two buoy lines, $d \in [0, 180)$,
(5) min degree d between any two buoy lines, $d \in [0, 180)$,
(6) max X difference between any two buoys,
(7) min X difference between any two buoys,
(8) max Y difference between any two buoys,
(9) min Y difference between any two buoys,
(10) max angle between X-axis and any buoy,
(11) min angle between X-axis and any buoy,
(12) average angle between X-axis and any buoy.

I used Multilayer Perceptron to train and test this Features dataset, the value of RRSE is 67.90%, compared to 82.12% this can testify our hypothesis is true to some extent. However, 67.90% is still not a good result, then I begin to research the Multilayer Perceptron, aim to reduce RRSE in algorithm aspect. After research, I found there are some parameters are very important for the Multilayer Perceptron, such as the Learning Rate, Momentum and Hidden Layers [10]. I proposed a hypothesis, it is that through adjusting the parameters, the RRSE can be reduced.

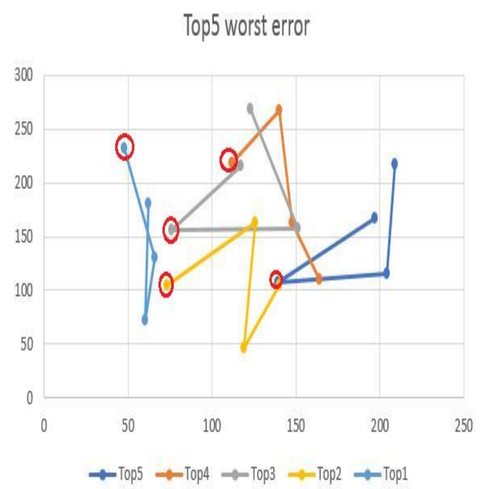
I used an experiment to testify this hypothesis. The method of this experiment is that first I changed the Learning Rate and keep other two parameters, I found when Learning Rate equals to 0.004, the RRSE is lowest. Second, keep the Learning Rate equals to 0.004 and Hidden Layers, change the value of Momentum. This time, when Momentum equals to 0.9, the RRSE is lowest. The last, I keep Learning Rate equals to 0.004 and Momentum equals to 0.9, change the Hidden Layers, when Hidden Layers is 12,10,8 which means Multilayer Perceptron has three hidden layers and the notes in each layer are 12, 10 and 8, the RRSE is lowest. The final RRSE is 50.97% [10]. Compare to my group members' machine learning algorithms, the Multilayer Perceptron has the best performance [10].

c. Bottleneck period.

After the first two phase, the RRSE is reduced to 50.97% from 80.12%, but it does not still make us satisfied. According to the hypothesis in phase A, if more attributes are added to the dataset, the RRSE probably be reduced. To testify whether this idea is right, I did some experiments according to the Figure 5. First, the (1) and (2) is the max and mix distance between any two buoys, respectively. I used every distance between two buoys to replace the (1), (2) and keep other same, the number of attributes increases to 16 from 12, however, the RRSE of this dataset is 55.13%, it is worse than 50.97%. Second, the (10) and (11) is the max and mix degree between X -axis and any buoy respectively, I used every degree between X -axis and any buoy and keep other same, the number of attributes increases to 14 from 12, but the RRSE is still not reduced which is 51.55%. Third, the features (6), (7), (8), (9) describe the coordinates of four buoys, I directly used every coordinate of four buoys to replace these four features, like the result of the first two experiment, this time the RRSE is also not reduced, it is 54.37%.

From these three experiments, I consider that the number of attributes just influence the RRSE in some extent. The more attributes the more accuracy, this idea is not right, in contrary, if the number of attributes is too much, it will make the input dataset too complex to predict the accuracy result. Another way to reduce the RRSE is to fix the source code. In the Multilayer Perceptron, the weight plays a key role. The input values are presented to the perceptron and if the predicted output is the same as the desired output, then the performance is considered satisfactory and no changes to the weights are made. However, if the output does not match the desired output, then the weight need to be changed to reduce the error. This means if I can change the weights of data which has a big error between predicted value and true value, the error can be reduced, in other words, the RRSE will be reduced. Although it is easy to see the source code of the Multilayer Perceptron, it is hard to understand what happens in the hidden layers, because it uses some deep knowledge of Mathematic. After trying several times, I gave up this way.

The research direction goes back to the datasets. Although I cannot change the weights, I can get the error between predicted and true of every data. In this way, I can get some worst errors and put their coordinates to 2-D coordinate axe to analysis why these coordinates bring the big errors. According to the WEKA API, I write my own Java code for analysis. Figure 6 shows the top 5 worst error for Feature dataset and their shape in 2-D coordinate axe. After analysis these shapes, it can be found that the coordinates which signed by a red circle are far away for other three coordinates, and they always in the left of other three coordinates, this probably is the reason why they have the worst error. I consider that it should think of the location of buoys in the actual situation. If we pick up one group coordinate from the top5 worst error and put them into the sea and if the wave direction is vertical and from left to right, then the outlier buoys should be subject to the power of the weave first. However, with our Feature dataset, we cannot simulate this process. I think if the machine learning model can get the almost same result with the Matlab model, it means that these two objects should be similar to some extent. After discussing this idea with group members, Mengyu proposed that we can sort the coordinates depend on different direction because our coordinates are generated randomly.



In addition, it is found that in our raw dataset the last two digits of true power value are always zero, however, the last two digits of predicted power are not zero, this probably is another aspect which can influence the RRSE. Then a high precision dataset which called Raw dataset with High Precision is generated for experiment

d. New progress

After the analysis in phase C, we sort the raw dataset and High Precision Original dataset in three ways: vertical, horizontal and basement. For both two datasets, the vertical way always has the lowest RRSE. The RRSE of the raw dataset which is lower precision is 19.37% and that of the High Precision Original dataset is 22.69%. Normally, we consider the higher precision dataset should have a lower RRSE, but the actual is the contrary. The reason I think is that the parameter configuration comes from the Feature dataset, so the previous parameter configuration probably is not suitable for the new dataset, so I need to try different parameters to check which is best. Before this experiment, I review the last experiment for the parameter experiment, I found that the last experiment is not religious because I only did five tests for each parameter and the experiment data is not continuous. For example, in last parameter experiment I used 0.1, 0.2, 0.5, 0.75 and 0.9 for Momentum, this is not religious because I jumped over some data such as 0.3 and 0.4. If the RRSE is lowest on the 0.3 or 0.4, I would miss that. To make my experiment more accuracy, this time I write my own Java code to test the parameters. It uses three loops for the test, the first loop tests the Learning Rate, the second loop tests the Momentum and the last loop tests the Hidden Layers. In addition, after study the Multilayer Perceptron, I found that the number of note in each hidden layer can bigger than the number of attributes. So, I also change the test range for the Hidden Layers. The result of the experiment is shown from the Figure 7 to Figure 9. As these Figures take up too much space, please check it in the appendix.

From these figures, it can demonstrate that at currently the best RRSE of the High Precision Original dataset is 21.29%, when the Multilayer Perceptron has two hidden layers and the first hidden layer contains 25 notes and the second layer contains 15 notes. The RRSE of the High Precision Original dataset is still higher than the Raw dataset, the reason can be divided into two aspects: One is that the number of notes in each layer is set lower or equal to 25. It is possible that the 26 can have a better performance. The second, because there is only a dataset if I can try 10 datasets and calculate the average, the result will be more credible.

In addition, after the project meeting with other departments, we are expected to use two buoys to train and test with machine learning algorithms, aim to make research easier. So, we generated a dataset which called Sorted dataset of Two Buoys. I still use the Multilayer Perceptron to train and test, the RRSE of this dataset is 2.89%. It can say that for two buoys, the RRSE is good enough for replace the Matlab model.

4. Evaluation

For software part, the performance of our web application need the evaluation. The main aspects are stability and concurrency. We can invite students to upload data file or train the model at same time to test the performance. And according to the performance to fix our web application.

For research part, there are two aspects which make our project hard to compare with the previous works which related to wave energy. First, the kind of input data is different. Our machine learning model does not need to simulate the process of wave energy conversion to compute the power output, this makes our input data simpler, which only contents the coordinates of buoys. The input data of the previous work is complex, it contains many parameters. Second, the benchmark is different. Our project chooses the RRSE as the benchmark, however, we do not yet find one study use the RRSE as the benchmark. It can say that our project is special, but we can evaluate by ourselves. Obviously, the benchmark RRSE is the lower the better, for 4 buoys dataset we reduce the RRSE from 82.13% to 21.29%, this is a big progress in this semester. However, compared to 2 buoys dataset which has a 2.89% RRSE, the four buoys dataset have not yet achieved the best performance. Compare to other machine learning modes which used by my group members, the multilayer perceptron currently has the best performance. Our target is to find a model which has a low RRSE no matter how many buoys are used, so we can compare the RRSE value from the different number of buoys to evaluate our model.

5. Next step

The individual plan for next semester still be divided into two parts:

For software part, the functions which did not finish in this semester will be implemented in the next semester. Such as the comparison of the performance of different machine learning components. I will work together with my group member to implement them. In addition, the UI of our web application still need to optimise and the more machine learning components will be integrated into our web application. Furthermore, some new functions, such as the forum, will be added to our application to provide a platform for some people who are interested in this aspect, if it is needed. At the same time, I will try more machine learning tools to assemble them to our web application. Furthermore, the security of our web application will be improved if it needed. Figure 10 shows the detail plan for next semester for software part.

Figure 10. Software part plan

Weeks	Contents
Week 1-2	Perfect SMS function; Perfect security.
Week 3-4	Implement comparison function; UI.
Week 5-6	Validation of uploaded files; Email notification.
Week 7-8	Integrate more machine learning components.
Week 9-10	Update the comparison function; UI.
Week 11-12	Test performance and fix.
Week 13	Quality review

For research part, although the RRSE of two buoys is low enough, the RRSE of the four buoys still stop at around 21%. How to reduce RRSE is an important topic for next semester. Here is a hypothesis, it is that we can use two buoys to optimise the four buoys, which means we regard four buoys are composed by two parts and each part contains two buoys, we find the optimisation power for each part, then regarding two parts as two buoys to get the optimisation result.

In addition, I plan to try more account of data. Because according to the previous study and my own experiment data, the more account of data can improve the accuracy of the model. And in the next semester, I plan to try 6 buoys to check whether our machine learning model is still suitable for it. For research work it is hard to establish a time table, because we not sure how much time we need to have a new progress. But I will try my best to push the project has a progress.

6. Conclusion

With the development of the renewable energy, wave energy become plays a more important role in global energy. Bases on the previous study researched by Ocean Wave Energy Research Group of Adelaide University, the purpose of our project is that we use the machine learning method to find the optimal result and we plan to develop a web App for data visualisation.

In software aspect, I implement the security of our website and work on the SMS notification function. I conclude that the main threatens come from password security, session security and SQL security. For each aspect, I set the defend measures to protect our web application and implement them in the backend. In research aspect, I focus on the Multilayer Perceptron to reduce the RRSE. For 4 buoys, the RRSE of it reduced to 21.19% from 82.13%, although this is not the best result, compared to 82.13% it already is a big progress. And for 2 buoys, the best RRSE is 2.89%, this is already a good result.

In this semester, through the effort of each group member, we not only have a big progress in the research part, but also in the software part. However, I think we still have more improvement space, in the next semester, I hope we can do better.

7. Appendix

Figure 7. Learning Rate - RRSE

Learning Rate	RRSE	Learning Rate	RRSE	Learning Rate	RRSE
0.1	53.78%	0.01	53.87%	0.001	55.89%
0.2	54.63%	0.02	53.55%	0.002	55.45%
0.3	58.24%	0.03	55.34%	0.003	55.41%
0.4	61.08%	0.04	55.37%	0.004	55.41%
0.5	68.56%	0.05	55.46%	0.005	55.42%
0.6	67.36%	0.06	53.44%	0.006	55.45%
0.7	67.01%	0.07	53.45%	0.007	55.48%
0.8	63.66%	0.08	55.8%	0.008	49.48%
0.9	128.37%	0.09	53.76%	0.009	53.87%

Figure 8. Momentum - RRSE

Momentum	RRSE	Momentum	RRSE	Momentum		RRSE
0.1	55.48%	0.01	55.93%	0.001		55.94%
0.2	49.49%	0.02	55.93%	0.002		55.94%
0.3	53.88	0.03	55.93%	0.003		55.94%
0.4	53.88%	0.04	55.93%	0.004		55.94%
0.5	53.92%	0.05	55.93%	0.005		55.94%
0.6	55.32%	0.06	55.94%	0.006		55.94%
0.7	55.29%	0.07	55.94%	0.007		55.94%
0.8	55.29%	0.08	55.94%	0.008		55.94%
0.9	53.79%	0.09	55.94%	0.009		55.94%

Figure 9. Hidden Layer – RRSE

Hidden Layer 1 Number of note	RRSE	Hidden Layer 2 Number of note	RRSE	Hidden Layer 3 Number of note	RRSE
6	44.11%	1	36.09%	1	38.91%
7	45.64%	2	30.76%	2	21.49%
8	41.8%	3	24.54%	3	31.17%
9	40.95%	4	27.14%	4	24.75%
10	40.19%	5	25.95%	5	29.05%
11	38.44%	6	24.75%	6	23.30%
12	43.56%	7	31.19%	7	23.60%
13	44.2%	8	27.67%	8	23.58%
14	32.56%	9	28.72%	9	30.01%
15	33.62%	10	22.84%	10	23.73%
16	29.09%	11	26.33%	11	24.79%
17	31.62%	12	25.07%	12	37.39%
18	36.81%	13	26.12%	13	31.95%
19	29.63%	14	21.34%	14	24.38%
20	34.22%	15	21.29%	15	24.61%

21	33.28%	16	28.07%	16	27.09%
22	32.16%	17	25.72%	17	27.12%
23	33.66%	18	25.47%	18	35.31%
24	39.6%	19	22.14%	19	28.49%
25	26.92%	20	22.32%	20	33.20%

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