# Review of Machine Learning Algorithms for Predicting Power Requirements for Unmanned Marine Vehicles

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## Introduction

Unmanned Marine Vehicles (UMVs) are used for missions like carrying out surveys in water, search and rescue etc. These UMVs are operated on rechargeable batteries, so it is important to predict the battery/power requirements for these UMVs beforehand so that they can successfully complete their assigned missions without exhausting their batteries in the middle of the mission. When it comes to energy requirement prediction for unmanned vehicles, two paths can be followed. In the first approach, a model is built which incorporates all the measured quantities that quantify the degradation of the system (e.g. in our case, these quantities can be wind forces, lift and drag forces that result in power consumption), and implements mathematical equations to estimate the power requirements. This approach uses a physics based model which requires lot of mechanical parameters and may be quite noisy for prediction. Second is a machine learning approach in which the features are defined that can possibly affect the system, and then based on the past experiences of the system, the predictions are made in the future based on the features. In both cases, historical data is needed. This paper focuses on the second approach and reviews the literature to discover machine learning algorithms that can be helpful in predicting the energy requirements for unmanned marine vehicles in different missions.

[2] has presented the features that can be used to build the machine learning models for predicting energy requirements for marine vehicles. It deals with the issue of predicting the ship's fuel requirement versus speed curve taking into consideration different weather conditions. It provides a good contribution to our research as it guides the feature selection for our research study.

There are not a lot of published works that directly focuses on predicting power requirements for unmanned marine vehicles but there are published works available from which the analogy can be taken to address our problem. For instance, [1] addresses the problem of predicting rate of oxygen consumption during maximal exercise, [3] deals with the issue of predicting power output generated from wind turbines. This paper attempts to classify these different independent studies which are analogous to our context and analyze the types of machine learning algorithms that these problems use for their prediction.

## Analysis of Algorithms

[1] deals with the problem of predicting maximal oxygen uptake (maximum rate of oxygen consumption) that would be required in different exercises. The most important features that it reports in its study are time, speed and grade (inclinations while running offering resistances to the subject). This study can be considered as an analogy to our problem of predicting rate of power consumption for UMV in different missions, as this also includes features like UMV speed and resistances from wind and water. Both of these problems can be classified into supervised learning category. Prior to [1], some studies have used Multiple Linear Regression (MLR) to solve these kinds of problems and they also reported lower SEE (Standard Error of Estimate) values and high R (correlation coefficient), but they implemented the algorithm on a very small dataset (for instance, dataset of length 26). So, that is why the efficacy of the MLR algorithm in this context is skeptical since, in practice, MLR needs large amount of dataset to produce high R. [1] implements and compares four machine learning algorithms on its reasonable length dataset namely, Support Vector Machines (SVM), Generalized Regression Neural Networks (GRNN), Radial Basis Function Network (RBFN) and Decision Tree Forest (DTF). The paper implemented these algorithms on 15 different models each with a different set of feature selection. The results show that, although, in general, the performance of GRNN based prediction models is slightly better than the SVM, but for some models (feature set) SVM performed better. From the results, it can be concluded that depending upon the selection of feature set, both the Artificial Neural Networks (specifically, GRNN) and SVM algorithms work reasonably well for these kinds of problems.

Another analogy can be taken from the research studies dealing with dayahead prediction of the output wind power from the wind turbine using machine learning techniques. Here, also many studies have applied different types of machine learning algorithms to predict the generated wind energy but the algorithms that have been proved successful for this type of problem are Artificial Neural Networks and Support Vector Machines. [5][6] reports a good performance in predicting the output wind power using SVM. SVM works by mapping the historical data into a higher dimensional feature space via non linear mapping (using kernel functions) and then the linear regression is used in the high dimensional feature space to train SVM and to predict the future values, which is equivalent to solving a non linear regression problem in the low dimensional feature space of the original problem. [5][6] implement SVM using two kernel functions- traditional RBF and their newly proposed wavelet function. The results show that, in general, both have good performances for this problem with wavelet slightly better than RBF. In our context of UMV, the wavelet kernel function would take the input data i.e. wind speed, current speed, sine or cosine of wind and current directions etc. as a non stationary time series and decompose it into a stationary series in different frequency bands using wavelet decomposition, and then these predicted results of frequency bands would be combined to form the final result. This wavelet kernel function may prove very useful for our problem when we want to predict real time power requirements during the execution of the mission since in this case, our power requirement values are non stationary and continuously changing with time, whereas RBF function would be useful to estimate power/energy requirements for the mission before starting the mission.

However, [3] shows SVM regression may deteriorate in terms of prediction accuracy when more input parameters are considered. The other technique is based on Artificial Neural Networks, which [9][10] have implemented in their studies. ANN models are based on the principle that the perceptions obtained through historical data are reflected on future predictions using the logic of neural systems. Since the problem of power prediction for UMV has non linear structure which needs to obtain a correlation between the wind speed/direction, UMV speed/direction, Current speed/direction and the required power, ANN models are suitable for this kind of problem [4]. But [7] shows that the performance of ANN and SVM is directly proportional to the amount of training data. However as the size of the training data set increases, ANN models take more computation time to learn the data.

There are studies available that employ a combination of different techniques in an effort to get the maximum possible prediction accuracy [8]. The simplest method of combining is simple averaging where all combination members are assigned equal weights, and the final combination is simply an arithmetic mean of alternative predictions. The drawback of simple averaging is its high sensitiveness to extreme values. Regression is another such technique which is employed by [3]. It assigns optimal weights to individual component predictions by minimizing the combined prediction's Sum of Squared Errors (SSE). This way it ensures that a model with larger prediction error gets less weight and vice versa. [3] implements SVM, ANN (Conventional Feedforward Network), Simple Averaging and Regression, and compares them on Normalised Mean Squared Error (NMSE) metric as shown in table1. [4] implemented the weighted average combinations of ANN and SVM models which yielded the minimum prediction error for their model.

| ML Technique | Mean Absolute Error | NMSE(%) |
|---|---|---|
| SVM | 43.59 | 3.17 |
| ANN (CFNN) | 34.53 | 1.65 |
| Simple Averaging | 32.97 | 1.58 |
| Regression | 28.31 | 1.03 |

Table1: Comparison of ML techniques [3]. The Results show that the Regression technique resulted in the best accuracy and it outperformed all the other techniques clearly.

## Conclusion

For the kind of a prediction problem that we want to solve, the two main algorithms or machine learning models that may prove highly effective are: Artificial Neural Networks and SVM. The critical point in using both these models is to select the best structure and parameters. With an improper structure and parameter selection, the error of the forecast model may increase to unexpectedly high values [4]. For a good prediction with ANN model, the selection of hidden layer number of neurons is very important. For a very few number of neurons, ANN cannot fit the data properly. On the other hand, if too many neurons are used, ANN over fits the data, which results in high error values. During training of the ANN model, mean square error (MSE) is used to obtain the model performance and weight/bias parameters of the network.

SVM models map data to higher dimensional space to obtain accurate results for a target problem. For a support vector regression problem, as in our case, the low dimensional space without SVM is equivalent to a linear one when mapped to a high dimensional space. The kernel function is selected after trial of all possible kernel functions in the prediction models.

However, there exists limitations for both the models. The effectiveness of the SVM decreases as the size of the input parameter increases. Both of the algorithms need quite a large amount of data since their performance depends highly on the size of the training data set. But ANN gets computationally less efficient when the size of the training dataset increases. It takes more time to learn and predict which cannot be tolerated in case of predicting power requirements for UMV. For some input parameters, SVM may prove successful and for others ANN would do. So then, people in the past have applied combination techniques to get the best out of these two algorithms and improve the overall performance of the model.

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