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MACHINE LEARNING BASED MAXIMUM POWER POINT TRACKING IN TIDAL/OCEAN ENERGY CONVERSION SYSTEM

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Abstract - In this paper, an efficient and supervised algorithm is presented to estimate a maximum power point (MPP) in Tidal/Ocean energy conversion systems by the implementation of machine learning (ML). Tidal energy extracted from the turbines depends on ocean current speed, tidal height, sea temperature, up cross period which most artificially intelligent algorithms such as neural networks ignore. Hill climb search is the most common and accurate methodology to track the maximum achievable power (MAP). However, the convergence speed to the maximum power point varies immensely and is slow. The proposed method uses machine learning to estimate a MPP using ocean current speed, sea temperature, up cross period and tidal height as input variables at every iteration. This MPP is then passed to the conventional hill climb search algorithm (HCS) to retrieve the MAP thereby reducing the perturbation time by a significant amount. At the end of each iteration, the machine learning algorithm is updated with the correct MAP thus avoiding overfitting which is predominant in artificial neural networks (ANN) and deep learning systems. The accuracy of the estimation increases after every iteration. Thus, for every tracked power point, the system is being trained recursively to predict an accurate MPP in the subsequent iterations. The simulation performed yielded an efficiency of 99.99% in estimating the MPP after 2500 iterations which corresponds to 9 hours of data.

Index Terms - Artificial Intelligence, Hill climb search, Machine, Learning Maximum Power Point Tracking, Tidal energy conversion.

I. INTRODUCTION

In this era of high energy requirements, most demands are sustained by fossil fuels. Overuse in this domain leads to major threats like global warming due to the excessive emission of greenhouse gases as by-products. There is a need to switch to renewable sources of energy. Ocean energy, if utilized efficiently has potential to be a substitute and can help with the world's energy crisis due to its abundance. Tidal energy is a form of hydropower that converts energy from the natural rise and fall of the tides into electricity. Tides are caused by the combined effects of gravitational forces exerted by the moon, the sun and the rotation of the earth. Tidal plants can only be installed along coastlines. Coastlines often experience two high tides and two low tides daily. The difference in water levels must be at least five meters high to produce electricity. Energy can be generated using several technologies, major ones being tidal barrages, tidaldefenses and tidal turbines. Tidal barrages are the most efficient tidal energy sources.It consists of a dam that utilizes the potential energy generated by the difference in height between high and low tides. This energy rotates a turbine or compresses air which in turn creates electricity. Tidal turbines are like wind turbines only underwater. In both cases electricity is generated by the mechanical energy of tidal currents turning turbines connected to a generator. Ocean currents generate relatively more energy than air currents because water is 832 times denser than air and therefore applies greater force on the turbines. A tidal power system is easy to install and renewable. having low environmental impact because the oceans tidal patterns are well understood. The tidal energy is a very predictable energy source making it attractive for electrical grid management. However, adoption of tidal technologies has been slow and so far, the amount of power generated using tidal power plants is very small. This is largely due to the specific site requirements necessary to produce tidal electricity. Additionally, tide cycles do not always match the daily consumption patterns of electricity and therefore do not provide sufficient capacity to satisfy the demand.
During high tide, the tidal wave rotates the turbine fan to generate a torque. The generator uses variable load to efficiently use the kinetic energy and maximize the output power supply. Maximum power point tracking (MPPT) is carried out by designing efficient charger controllers for extracting maximum available power (MAP) from the ocean tides. The charger controller is designed to control and optimize the generated power. Various methods like hill climbing search (HCS) [1], method of Incremental Conductance [2], method of Fractional Voltage [3], Neural Network [4] and fuzzy logic control [5] etc., are used in charger controllers to generate efficient power outputs. These algorithms have been compared based on complexity, efficiency, performance, etc., and are listed in Table I.

In this paper, an alternative approach to the existing methods has been suggested to overcome the limitations in terms of efficiency and performance. The proposed design uses machine learning (ML) prior to HCSmethodology to get the maximum power point (MPP). This essentially increases the performance on a large scale. Machine learning is an artificial intelligence that providesa system the ability to learn without manually programming. It focuses on the developing software programs that can learn on its own and vary on exposure to new set of data. Results have been compared with the existing methods based on efficiency and performance. However, at any instant of time when the tide changes, several of the mentioned methods are slow to adapt the system parameter to draw the most efficient amount of electric power.

Table I: Comparison of different MPPT techniques [6]

MPPT Technique	Speed of Convergence	Complexity	Periodic Tuning	Sensed Parameters
Perturb and Observe	Varies	Low	No	Voltage
Incremental Conductance	Varies	Medium	No	Voltage Current
Fractional V_{oc}	Medium	Low	Yes	Voltage
Fractional I_{sc}	Medium	Medium	Yes	Current
Fuzzy Logic Control	Fast	High	Yes	Varies
Neural Network	Fast	High	Yes	Varies

II. SYSTEM MODEL

Fig. 1 describes the working of the MPPT algorithm. The system model comprises of a self-excited DC generator, the conventional hill climb search block, a DC - DC buck converter and the ML block.

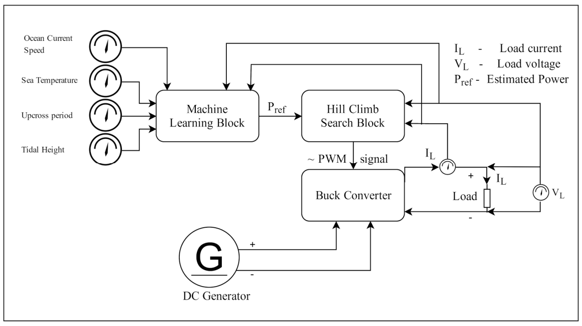


Fig. 1 Proposed Tidal/Ocean energy conversion block

A. Machine Learning based Estimation Technique

The Machine Learning block accepts 4 inputs (ocean current speed, sea temperature, up cross period, tidal height) to estimate a MPP (P_{ref}). This estimation is made using a decision tree regression model. In this paper, ID3, or Iterative Dichotomizer algorithm is used [7]. For the given input parameters, a decision tree is built, beginning from a set of objects (the input variables) and a description of properties, resources and information. Each of the property is analyzed based on maximizing information gain and minimizing entropy based on Shannon's Entropy [7], and the results are used to divide the dataset. This process is recursively performed until the data set in each sub-tree is homogeneous. The input variables are transformed and an algorithm for estimation of the reference point (P_{ref}) is thus created at every iteration. The HCS module starts the perturbation from P_{ref} as compared to the zero position in a conventional module. The obtained maximum power point is sent to a buck converter which is connected to the DC generator. It gives optimal output to the connected load using a pulse width modulation (PWM). The subsections below explain detailed working of each of the components described.

B. Separately Excited DC generator

A DC generator converts mechanical energy (P_m) to electrical energy. The mechanical power fed into the rotor by the tide appears as kinetic energy of the rotor blades [6].

$$P_m = \frac{KE}{t} = \frac{1}{2}\rho A v^3 \qquad (1)$$

where, ρ is the fluid density, A is the area covered under turbine blade and v is the fluid speed. However, there is a theoretical limit to the amount of power that can be utilized practically. This limit is set by Betz's Law [8]. It states that a turbine can only capture a maximum of 59.3% of kinetic energy of the fluid. Therefore, the power generated depends on an efficiency factor, also known as coefficient of performance $C_p(\lambda, \beta)$ of the turbine. It depends on the pitch angle (β) and the tip speed ratio (λ). Tip speed ratio is the ratio of turbine speed to the fluid speed.

$$\lambda = \omega\frac{R}{v} \qquad (2)$$

Here ω is the angular speed of the turbine and R is the radius of the blade. Therefore, the power generated is given by

$$P = C_p(\lambda, \beta)P_m = \frac{1}{2}C_p(\lambda, \beta)\rho A v^3 \qquad (3)$$

The coefficient of performance is given by [9]:

$$C_p(\lambda, \beta) = 0.5\,(116\frac{1}{\lambda_i} - 0.4\beta - 5)e^{-21/\lambda_i} \qquad (4)$$

where β is the pitch angle and $\frac{1}{\lambda_i}$ is given by,

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{1 + \beta^3} \qquad (5)$$

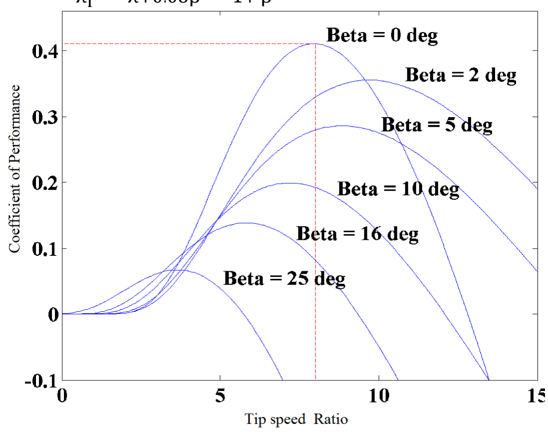


Fig. 2 shows the coefficient of performance verses tip speed ratio for different values of β [10].

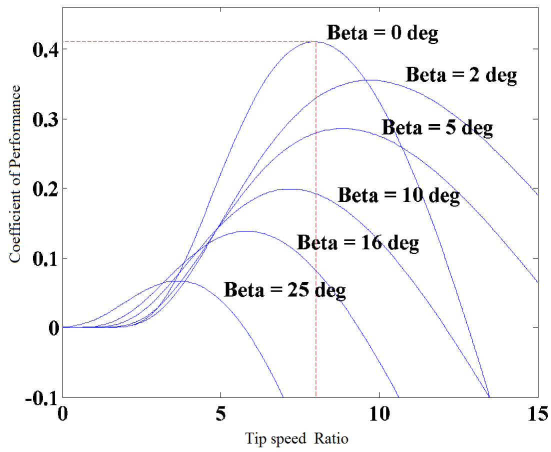


Fig. 2 Coefficient of performance vs λvs β

C. Hill Climb Search Method

The charger controller block estimates a reference Maximum Power Point (P_{ref}) based on previous iterations. The HCS [11], [12] blocks start the perturbation from this (P_{ref}) and reads the external load circuit parameters (voltage and current) and compares it with the input reference. A decision is then made to increase or decrease PWM based on the comparison and starts the next iteration. A flowchart on the working of the algorithm is show in Fig. 3, where P_i is the calculated power in the current iteration and P_{i-1} is the power output for the preceding iteration. The algorithm ends with sorting the obtained MAP from HCS to the input variables and appending the ML algorithm at every iteration.

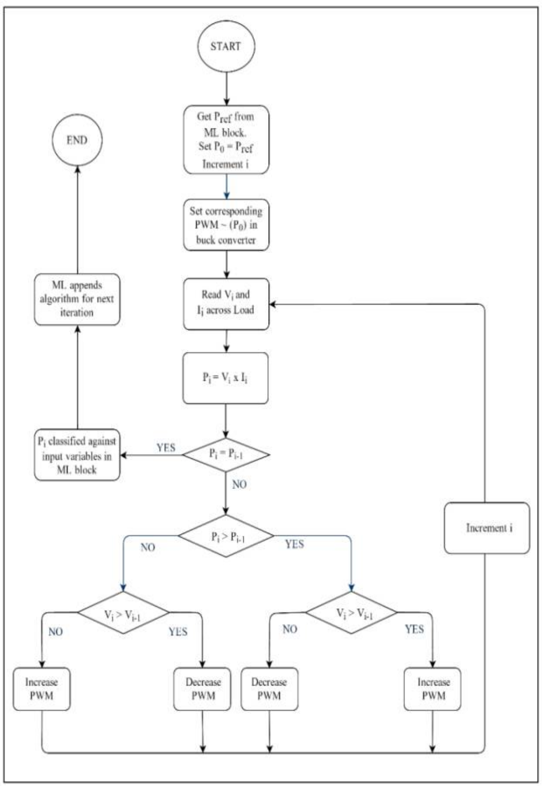


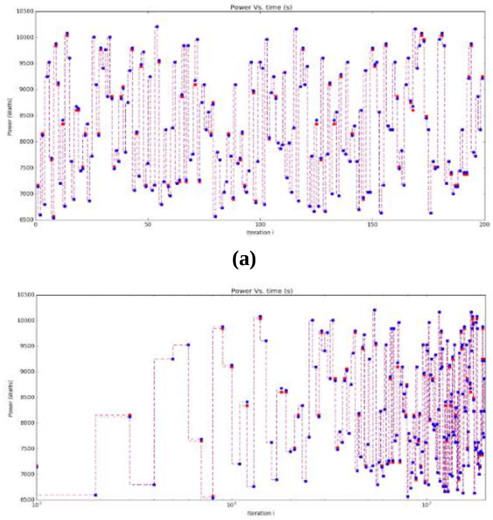
Fig.3 Flowchart depicting P&O algorithm

D. Buck Converter

A buck converter [13] is a DC to DC converter which increases current while stepping down voltage simultaneously from the input supply to the load or vice versa. Buck converters have high efficiency (up to 90 %).The PWM signal generation by the HCS block is used as a control signal input to the buck converter as shown earlier in Fig. 1.

III. RESULTS

A graph of estimated P_{ref}(red) versus actual maximum power point MAP (blue) is plotted in Fig.4a. It shows that the estimation of the MPP (P_{ref}) is very close to MAP. These results were retrieved after 2500 iterations. Fig 4.b shows the logarithmic graph of the same. Each step depicts each iteration i.



(a)

(b)

Fig. 4 Estimated PowerP_{ref} (red) and MAP (blue).

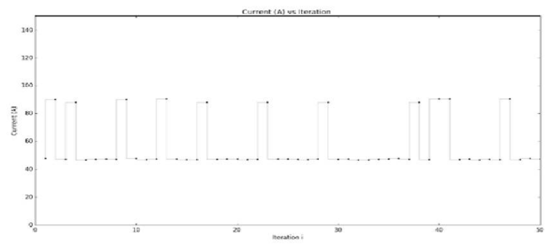


Fig 5. Current Vs Iteration i

Fig. 5 and Fig. 6 shows the dynamic responses of current and voltage respectively.

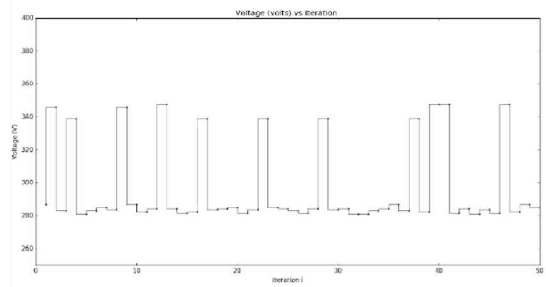


Fig. 6 Voltage Vs Iteration i

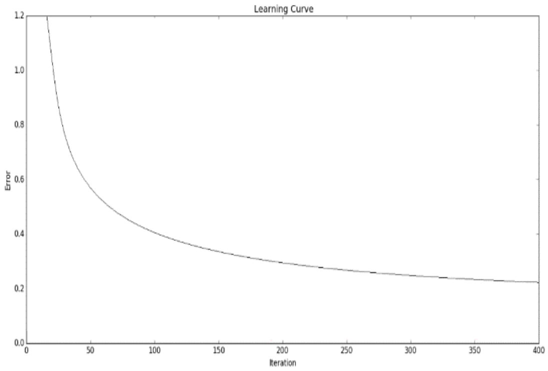


Fig. 7 Learning curve of decision tree regression model

Fig. 8 shows that the efficiency of the algorithm is increasing with every iteration. The learning curve shows that the efficiency is almost 99.97% after 400 iterations. At the end of 2500 iterations, the efficiency was observed at 99.99% as shown in Fig. 8.

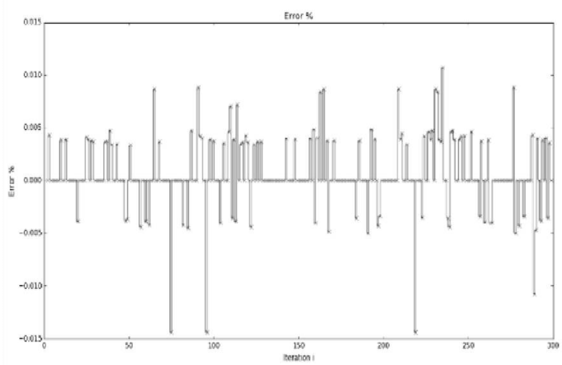


Fig. 8 First 100 iteration-errors after 9 hours

The figure describes that the error percentage at every iteration after 2500th iteration. It is at 0.01% which makes the model accurate and precise to the 4th decimal point.

IV. ADVANTAGES OF USING MACHINE LEARNING

ML based HCS has a much faster convergence to the MPP than regular HCS. The proposed system is highly efficient and continuously learns and adapts to the weather compared to other artificial intelligence based algorithms such as neural networks and deep learning algorithms which do not provideenough accurate resultsdespitebeing fast. Misclassifying input data points by simply adding small perturbations to the input can confuse a deep learning algorithm or predict inaccurate values. These oscillations practically occur in every measurement. This doesn't affect the learning phase in the case of the proposed method as there is always a supervised learning involved. Neural networks add hidden layers which result in the much higher complexity of the results regarding the time taken for estimation without any supervision. The characteristics of the proposed algorithm is mentioned in Table II.

TableII Comparison of MPPT techniques with ML

METHOD	LEARNING PHASE	COMPLEXITY	ACCURACY	TIME TAKEN
Proposed Method	YES (Supervised)	HIGH	HIGH	LOW
Perturb and Observe	NO	LOW	HIGH	HIGH
Fuzzy Logic control	NO	HIGH	MEDIUM	MEDIUM
Neural Networks	NO	HIGH	MEDIUM	MEDIUM

CONCLUSION

In this paper, a new and efficient method to generate maximum power from ocean/tidal energy conversion systems in varying weather conditions using machine learning is described. A python simulation was carried out to obtain the results by feeding in a decision tree regression model using ID3 algorithm which tracks changes in the water flow rate. The accuracy and performance of the proposed method is not affected by the variations in input data or minor fluctuations. The time for perturbation decreases with every iteration as the algorithm continuously adapts to the versatile conditions. This supervised model overcomes overfitting observed in other artificial intelligence based algorithms such as fuzzy logic control, artificial neural network, etc. The major advantage of the proposed method of MPPT control is robustness, faster convergence to the MAP, higher efficiency and its ability to learn constantly with each iteration. The system is an optimized algorithm of HCS method and hence can be cascaded as a charger controller to the existing HCS equipment thus resulting in much faster convergence speeds.

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