Offshore Wind Energy Transmission with Multi Terminal High Voltage DC grids (MT-HVDC) and Fuzziness

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The following is an document written by Daniel Lewis and Tibin Joseph, it is written to be both informal and easy to understand. The intellectual property remains with the respective parties. It is, however, worth noting that the application of the X-mu models for error modelling are novel and original ideas of Daniel Lewis and Tibin Joseph. The existing models of fuzzy controllers are published elsewhere and will be referenced throughout the document. This document will be published openly and via the world wide web, and will be referenceable. An updated formal version may appear in future publications written by the authors.

Introduction

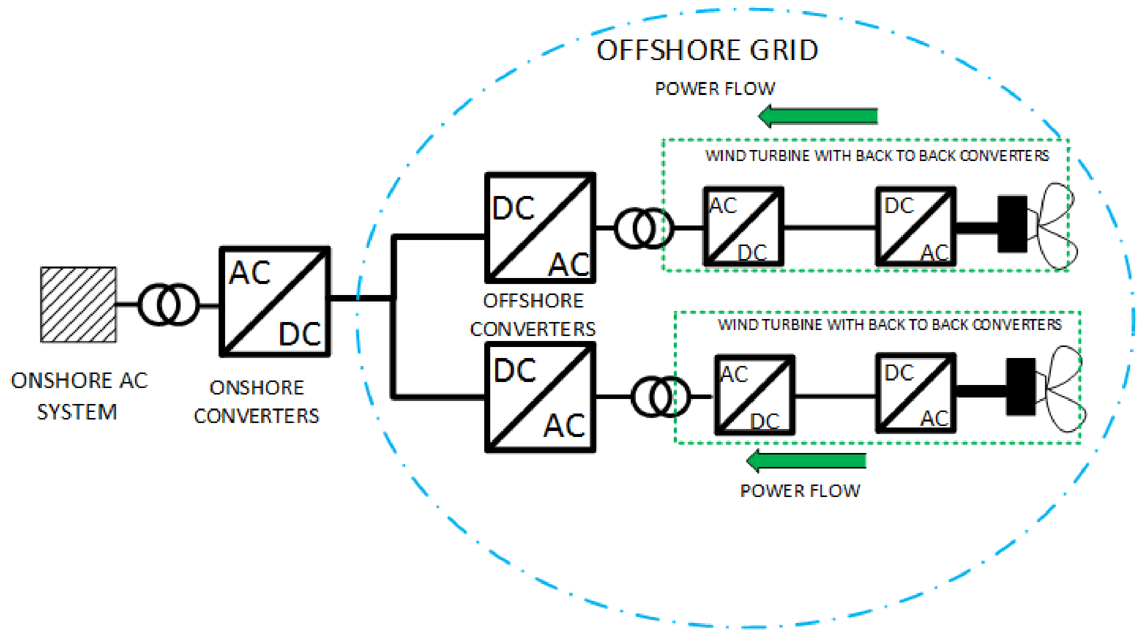
FUZZY logic has developed extensively ever since its inception by Zadeh [1]. Though the effectiveness of fuzzy logic has been proven in many instances in industry, the use of fuzzy logic in electrical power systems is still not widespread. One of the reasons for this limited application in the power system area could be the need for subjective and possibly unreliable (due complexities and nonlinearities involved) expert advice. In terms of robustness and relatively simple implementation and design, fuzzy logic has many advantages. It suffers, though, from one major criticism. The design of fuzzy logic controllers (FLCs) depends heavily on experience namely, the experience of a human expert/operator. This means that the design process is largely dependent on having a priori information about the system behavior.
But the application of FLC in power system is getting widespread increase due to its adaptability with high nonlinearities, and applicability in systems where model is unknown or even mathematically complex. Power system is such a highly nonlinear system and with the increased integration of Renewable Energy Sources (RES) like wind, solar PV etc.), the control of the system operations becomes increasingly difficult and the use of a nonlinear controllers like FLC are gaining wide spread applications

Existing work in Offshore Wind Energy Control

Large wind farms are generally connected to the grid through AC transmission lines. However, long distance transmission and recent emergence of off-shore wind farms has led to the use of HVDC for the grid interconnection of such wind farms. The HVDC system traditionally uses PI controllers to control the dc current thereby keeping the power order at the required level. Although, these controllers are no doubt robust and are operating satisfactorily since many years, they are prone to changes in system parameters, delays or other non-linearities in the system and suffer some limitations

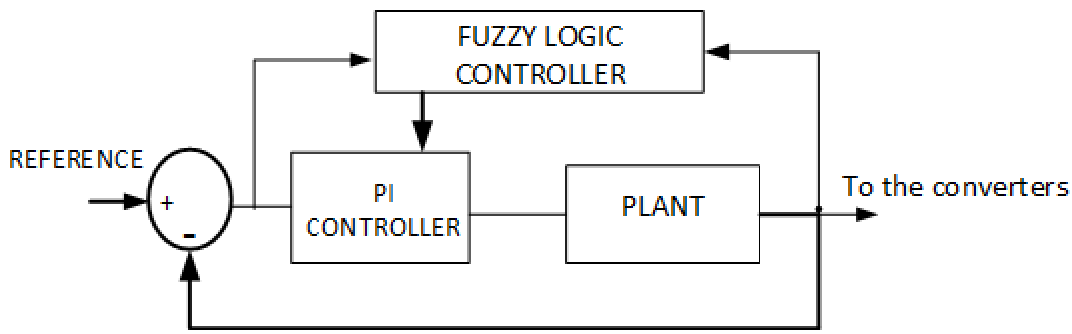
Voltage Source Converters (VSC) are one of the most used converters in offshore wind farms and HVDC systems, since a VSC can operate as either inverter or rectifier. Furthermore, a VSC allows fast, accurate and independent active and reactive power flow control. However, a VSC is a double- input double-output non-linear control object, therefore; nonlinear control strategies can be useful in order to obtain desired behaviours. Generally PI controllers are used at VSC HVDC stations for the power flow and DC voltage control. Those controllers are tuned to one or more operating conditions. When a VSC HVDC is connected to a wind farm, disturbances in the power

The figure below shows a three terminal network, where two offshore terminals are connected to wind farms and the onshore VSC converter is connected to the AC system. The harvesting of wind power from the sea is presented with VSC converter based HVDC system used for transmitting that power to the AC grid which is onshore



The control block diagram of the proposed system with application of FLC to tune the conventional PI controller is shown below. This method can be more effective because of the uneven or fuzziness in the wind flow, there by the wind power injection into the AC grid. The FLC controller can be used to minimize these variation and the quality and security of supplied power can be improved. The improved tuning of the conventional controller and the application of that in the proposed system is what we are expecting to do in the near future. The existing methodology will be reviewed and the effectiveness of those will be compared with our proposed X mu fuzzy approach

S. M. Muyeen et al has used the FLC based approach to increase the power transfer from a VSC based offshore wind farm, which shows the effectiveness and practicality of the proposed method. But the use of FLC in a MT-HVDC control is yet to be discovered and needed more in depth studies and analysis



The X-mu Approach to Fuzziness

Traditional fuzzy set theory, as conceived by Lotfi Zadeh in the 1960s onwards, states that something can have a classification (or category) to a degree. It therefore establishes “shades of grey” that a computer can understands, along with techniques for using and manipulating those “shades of grey”.

For example, a red ball might not be perfectly red and might not be perfectly spherical, it will, however still be classed as a “red ball”. Another example might be the idea of “heavily raining”, which might be measured by millimetres of rain per hour, its distinction with “moderately raining” is what we call fuzzy.

In traditional fuzzy set theory we often take a measurement (such as rainfall) and convert that to a value between zero and one called a membership value (or the greek letter μ, sometimes written as “mu”). The conversion process is what we call a membership function.

What we call the “X-mu approach to fuzzy sets” was defined by Trevor Martin and Daniel Lewis, and reverses the conversion process (which is roughly equivalent to making a partial inverse function in mathematics). This means that our X-mu membership function takes in a value between 0 and 1 (i.e. a membership function) and returns a set of all values that are interesting (i.e. those in our “domain” or “Universe of Discourse”). It is important to note that the X-mu approach is best coupled with symbolic computation, which means we use variables as much as possible (this is a simplification). The reason for this is because we can manipulate algebraic formulae very easily and this retains much of the meaningfulness of an X-mu membership function. There are other benefits to the X-mu approach, particularly when we talk about fuzzy set difference (simplistically, minusing one membership function away from another), however, this is beyond the scope of this particular document.

In order to put the X-mu approach into practice, a software library was developed in the python programming language. A software library is a pluggable piece of software which allows for software to be created easily using the functionality of that library. The python programming language is an interpreted language that is both an object-orientated language (and so it works well with software libraries) and a functional language (and so works well with mathematical formulae). The X-mu Python Library was written by Daniel Lewis, and is available for use as free and open source software, it is available at: https://github.com/danieljohnlewis/xmu-python

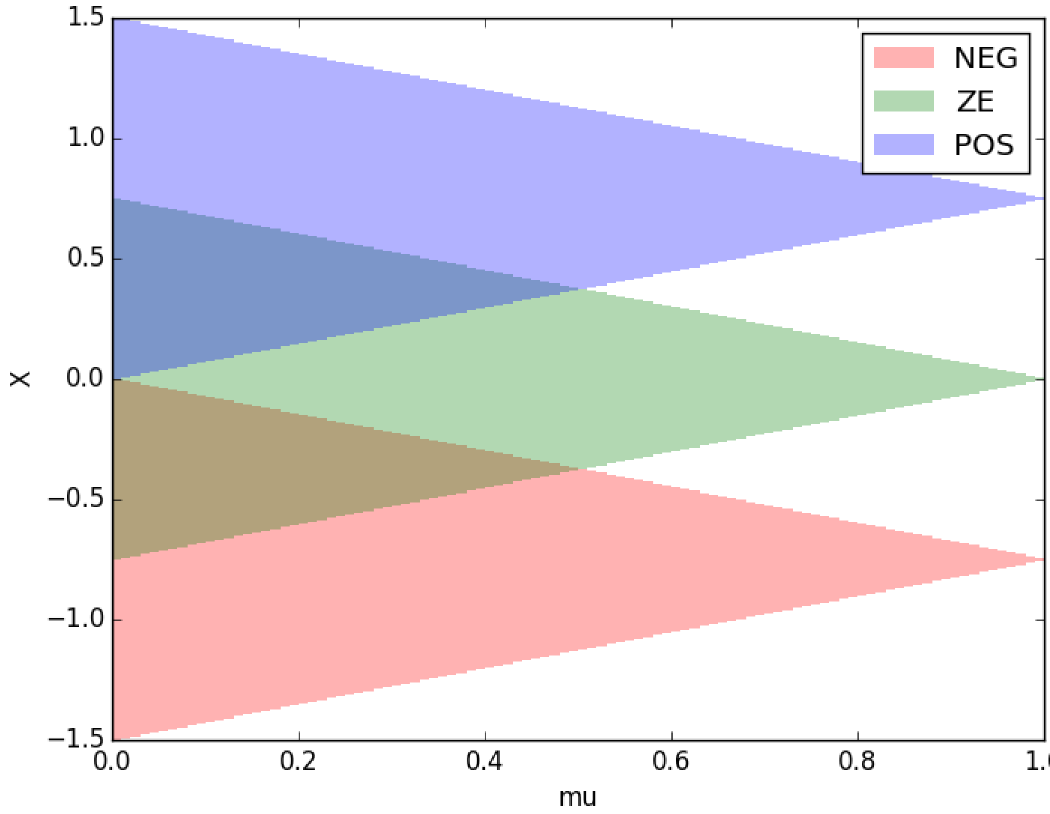
Modelling error using the X-mu Approach to Fuzziness

Taking the membership function for m_{error} as defined by Narendra et al in 1997, the following python code which uses the X-mu Python Library can be written:

```
1.from xmu import *
2.
3.u_error = Interval(-1.5, 1.5)
4.
5.m_error_neg = TriangularXmu(u_error, -1.5, -0.75, 0.0)
6.m_error_ze = TriangularXmu(u_error, -0.75, 0.0, 0.75)
7.m_error_pos = TriangularXmu(u_error, 0.0, 0.75, 1.5)
8.
9.error_graph = Graph(100, u_error)
10.      error_graph.prepare_plot(m_error_neg, u"NEG", colour="r")
11.      error_graph.add_plot(m_error_ze, u"ZE", colour="g")
12.      error_graph.add_plot(m_error_pos, u"POS", colour="b")
13.      error_graph.show_plot()
```

To summarise this simply this models the NEG, ZE and POS of m_{error} using the X-mu approach to fuzzy set theory. The line 1 imports all functions from the X-mu library. Line 3 defines our “Universe of Discourse” between -1.5 and 1.5. Lines 5 to 6 establish three triangle shape X-mu membership functions using their low and high points. Lines 9 to 13 simply build a graph (with resolution 100) which represents those three X-mu membership functions.

The result is an X-mu graph:



Which is comparable to the m_{error} of Figure 3 in the 1997 paper by Narendra et al.

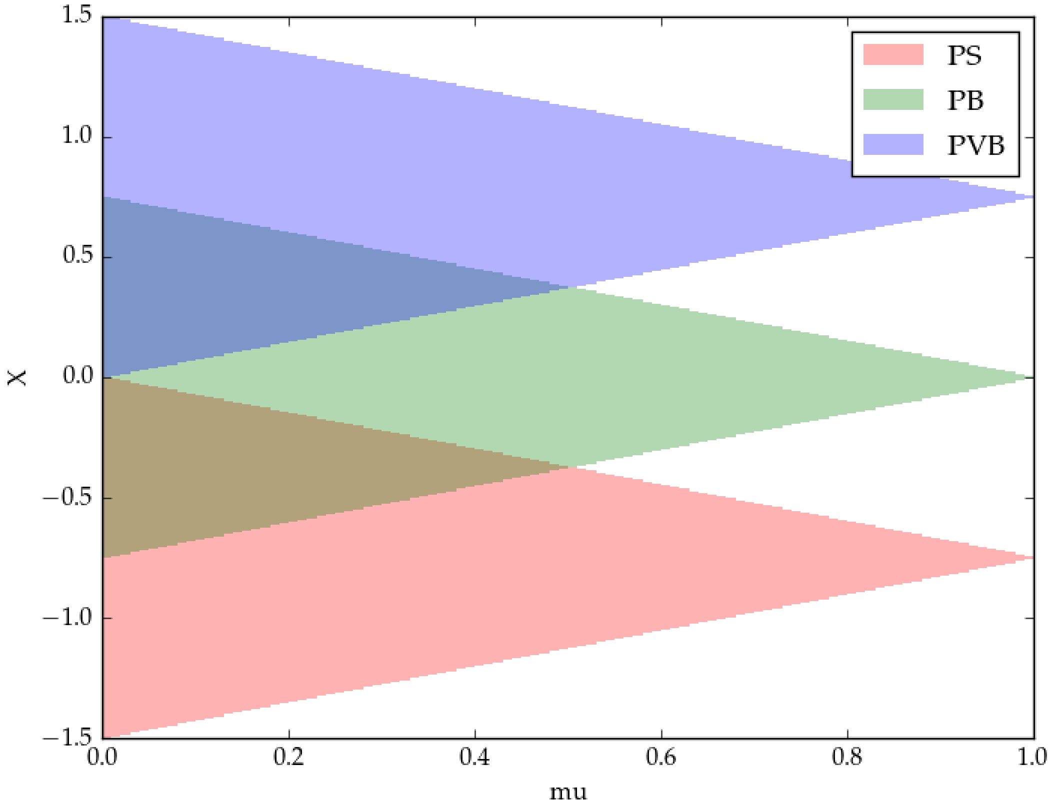
Mamdani Inference

In the Narendra et al paper of 1997 we see that Table 1 shows a Fuzzy Rule Base. The rules describe how to classify (or fuzzy classify) the error and the change of error in the intelligent current controller. These output classifications are used as learning parameters for an Artificial Neural Network and correspond to learning rate weight, momentum weight, learning rate slope and momentum slope. More details about that can be found in the Narendra paper.

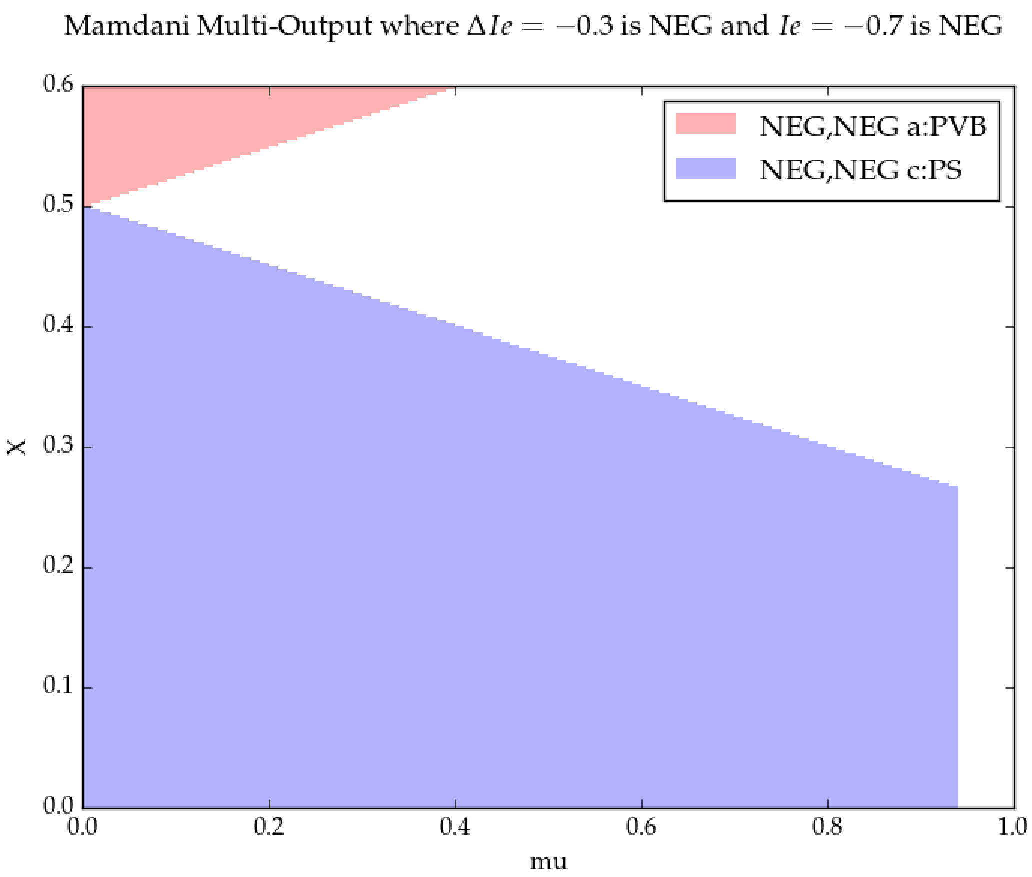
This Fuzzy Rule Base is put through a Mamdani fuzzy inference engine, which means the membership value (mu) of the inputs are put through an intersection (i.e. they are minimised, to find the lowest membership value out of the inputs), and then that mu value is then used to truncate the output fuzzy membership function.

In the case of the Narendra paper, we find that m_{error} and $m_{cherror}$ are inputs, as we know they turn error (Ie) and change in error (ΔIe) into membership values. The $m_{learningparameter}$ on the other hand is the membership function for the output values.

$m_{learningparameter}$ looks like this:



Once it has been through Traditional Fuzzy Mamdani Inference, using the X-mu approach, an example output looks like this - which is for the NEG-NEG rule in Table 1 of the Narendra paper for outputs a and c:



Conclusion

This is just the beginning really, and these models have yet to be included in any current controllers.

Much more work is required in making an X-mu Inferencing engine that is more semantically meaningful, and perhaps hooks into some of the benefits of the X-mu approach, particularly regarding X-mu set difference.

Work also needs to be done on a defuzzification method from an X-mu model into a single point to be placed within the larger control system. That aside, it would be highly beneficial if defuzzification did not occur, and perhaps there is some research to be done in the use of X-mu models directly inside of current controllers.

Acknowledgement

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