nationalgrid

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Network Innovation Allowance Progress Report

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Project Progress

Project Title	**Project Reference**
A Combined Approach to Wind Profile Prediction	NIA_NGET0039

Project Licensee(s)	**Project Start Date**	**Project Duration**
National Grid Electricity Transmission	Sep 2011	4 Years

Nominated Project Contact(s)

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Scope

The project will investigate the modelling of atmospheric behaviour and interaction between wind and turbine at the level of an individual turbine.

Objective(s)

The objective of this project is to cost effectively reduce the amount of reserve required to cover wind forecast error.

Success Criteria

- A final report describing prediction methodology and level of accuracy improvement achieved.
- Costs benefits evaluation of different degrees of modelling detail and associated reduction in forecast error.
- Modelling source code,

Performance Compared to the Original Project Aims, Objectives and Success Criteria

“NGET (“NG”) has endeavoured to prepare the published report (“Report”) in respect of “A Combined Approach to Wind Profile Prediction NIA_NGET0039” (“Project”) in a manner which is, as far as possible, objective, using information collected and compiled by NG and its Project partners (“Publishers”). Any intellectual property rights developed in the course of the Project and used in the Report shall be owned by the Publishers (as agreed between NG and the Project partners).

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Wind profile (including speed and direction) prediction at different scales (short-term, mid-term and long-term) plays a crucial role for efficient operation of wind turbines and wind power prediction. This problem can be approached in two different ways:

- Using statistical signal processing techniques and both linear and nonlinear models (such as artificial neural networks) can be employed either separately or combined together for profile prediction.
- Using computational fluid dynamics (CFD) in applied mathematics to model atmospheric flow. This is an extremely time consuming process with high computational complexity.

There is a need to improve forecast techniques to enable the optimum balance between sophisticated modelling and cost to be identified.
This project will develop efficient and effective algorithms for wind profile prediction based on synergies between the signal processing approach and the CFD approach.

We planned to finish the project in three years, with three major stages: study the signal processing approach to wind profile prediction (one year); study the CFD approach to wind profile prediction (half a year); finally developing efficient methods by combining these two together to achieve a balance between sophisticated modelling and cost (one and a half year). However, due to reasons explained later, we have to spend much more time at the first stage and need to extend the project period from three years to four years.

The focus of the first two years of the project have been on developing quaternion-valued signal processing methods and algorithms for linear prediction, which is the most difficult part of the project. A quaternion number has four components, one real part and three imaginary parts. Unlike real and complex numbers, in general the product of two quaternions depends on the order, i.e., q times p is not equal to p times q, where p and q are two quaternions. This non-commutativity complicates the definition of some mathematical concepts and the derivation of some important mathematical operations.

Initially, we used the existing definition of quaternion-valued gradient operation and the derived quaternion-valued least mean square (QLMS) algorithm [1] in our study and published a conference paper for wind profile prediction in the frequency domain to increase the speed of the algorithm [2]. However, after detailed study, we found that the existing gradient definition and the derived QLMS algorithm were not consistent, mainly due to the non-commutativity rule was not strictly enforced in the academic literature up to that point. It appears that the authors used the traditional product rules as well as chain rules, which are valid only if non-commutativity is not strictly enforced, while the three dimensional quaternion model we used in our project is strictly non-commutative. As a result, we had to re-define the gradient operation and derive a new version of the QLMS algorithm, which admits the general product rules and chain rules. We then performed simulations to verify the derived algorithms and published two conference papers based on this new development [3][4]. One is about the newly defined general quaternion-valued gradient operator and its applications to computational fluid dynamics and adaptive beamforming [3]; the other one is to try to enforce sparsity in the obtained prediction parameters (i.e. some of the parameters are zero-valued) for low complexity implementation in sparse system identification [4].

In the third year of the project, we further expanded our findings in quaternion-valued signal processing and studied the various characteristics of the quaternion-valued gradient operator and explored its application in both linear and nonlinear adaptive filtering and prediction and one paper about this progress was published in the journal Frontiers of Information Technology and Electronic Engineering in February 2016 [5]. Moreover, we have also studied its application for low-power and low-complexity interference suppression for an array of sensors and the paper summarising these results was published in IEEE Trans. Circuits and Systems II in March 2016 [6].

Now a solid theoretical foundation for the project has been laid down and in the final year we have been focusing on the application side, i.e. applying the developed algorithms to the CFD data with a thorough feasibility study to show that a combination of the signal processing method and the CFD method will bring us the desired benefits as described in our original project proposal, i.e. much lower complexity (reduced computer running time) with a similar prediction accuracy. In the combined method, the signal processing part employs the QLMS algorithm, while for the CFD part, LES based on the Smagorinsky SGS model is employed. The alternating process is described as follows. First, the QLMS algorithm is used to obtain the predicted wind velocity, and then we use the prediction result as the initial conditions for the LES method for calculating the next stage of the wind velocity. In the next round, the same process is repeated. Now we have finished this part of the project and it has been shown by computer simulations that the combined approach really works by providing a similar prediction result but with only half of the running time required of the CFD approach, which indicates that it is a very promising route for further exploration. One draft conference paper has been completed and will be submitted to a future conference. In the future, a thorough study of this new method can be performed with its various extensions/variations investigated. One representative application example for the developed technique would be effective wind farm design.

[1] C. C. Took and D. P. Mandic, “The quaternion LMS algorithm for adaptive filtering of hypercomplex processes,” IEEE Transactions on Signal Processing, vol. 57, no. 4, pp. 1316–1327, 2009.

[2]. M. D. Jiang, W. Liu, Y. Li and X. R. Zhang, “Frequency-domain quaternion-valued adaptive filtering and its application to wind profile prediction“, Proc. of the IEEE TENCON Conference, Xi’an, China, October 2013.
[3]. M. D. Jiang, W. Liu and Y. Li, “A General Quaternion-valued Gradient Operator and Its Applications to Computational Fluid Dynamics and Adaptive Beamforming“, Proc. of the International Conference on Digital Signal Processing, Hong Kong, August 2014.
[4]. M. D. Jiang, W. Liu and Y. Li, “A zero-attracting quaternion-valued least mean square algorithm for sparse system identification“, Proc. IEEE/IET International Symposium on Communication Systems, Networks and Digital Signal Processing, Manchester, UK, July NIA_NGET0039 - Progress Report 2015 Created: 29 Jul 2015 Page 2 / 3 2014.
[5]. M. D. Jiang, Y. Li and W. Liu, “Properties and Applications of a Restricted HR Gradient Operator for Quaternion-Valued Signal Processing”, Frontiers of Information Technology and Electronic Engineering, Volume 17, Issue 2, pp 83–95, February, 2016.
[6]. M. D. Jiang, W. Liu andY. Li,“Adaptivebeamformingforvector-sensorarrays based on reweighted zero-attracting quaternion-valued lms algorithm,” IEEE Transations on Circuits and Systems II: Express Briefs, vol. 63, issue 3, pp. 274-278, March 2016.

Required Modifications to the Planned Approach During the Course of the Project

Changes to Cost

There has been a small increase in budget for this project to facilitate more dissemination of information about the progress of this project.

Changes to Programme

The project duration was extended to the end of August 2016.

Lessons Learnt for Future Projects

This project will generate learning in respect of the extent to which wind power generation forecasting accuracy can be improved with reduced complexity using CFD and signal processing, how much reserve to cover forecast error can be reduced and at what cost. The full methodology would allow optimal placement of turbines in any terrain and a better understanding of the air flow through the wind farm. There is great potential for learning the detailed behaviour of the wind farms under different atmospheric conditions and improving forecast accuracy greatly beyond the current levels.

Now, we have developed the correct definition for the gradient of a quaternion-valued function with quaternion-valued parameters and derived corresponding algorithms for adaptive signal prediction, and shown that the adaptive signal prediction method and the CFD method can be combined together to give a low-complexity solution to wind profile prediction. In particular, a new combined method is developed by alternating the operations of the QLMS algorithm and the LES method one by one. As demonstrated by computer simulations, the proposed method has a much lower computational complexity with roughly half of the running time of a standard LES operation, while still maintaining a comparable performance in terms of prediction accuracy. In the future, a thorough study of this new method need to be performed with its various extensions/variations investigated.

Currently the energy forecasting team have not adopted the learning in this project because the concepts are still at an early stage of development. It is hoped that the work done here will feed into the specification and delivery of a future forecasting system as part of the TAR-Map programme. Before that can happen there will need to be further work done to verify the accuracy of this technique sufficiently exceeds the accuracy of techniques currently employed in wind power forecasting. This will require more detailed verification by comparing the predicted results with real world measurements using LIDAR data from an operational wind farm. This work will form part of a future innovation project that will move this technology to a higher technology readiness level and prepare it for practical implementation