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Summary:
As the first part (three parts in total) of Aeolus deliverable D3.1, this report contains the results of the literature review by Industrial Systems and Control. The purpose of the review was the identification of the strategy for the nominal farm-level control of active power to be developed and implemented by Work Package 3.

Existing strategies for dispatching the wind-farm active power setpoint to the individual wind turbines are reviewed, in particular with respect to large wind farm applications. In addition, the basics of model-based predictive control technology and its application to several industrial problems, with characteristics similar to wind farms, are summarised.

It is concluded that model-based predictive control (MPC) is an appealing candidate for wind farm active power supervisory control, mainly due to its capability in performing online constrained optimisation, tracking a future reference trajectory and handling multivariable processes as well as processes with long dead-times. Nevertheless, several issues must be addressed in applying MPC to large wind-farm control, including nonlinearities, cost functions, disturbances and scalability.

Aeolus

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Deliverable 3.1

Control Strategy

Review and Specification:

Part 1 – Nominal Control Review

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Executive Summary

This report forms the first part (three parts in total) of the Aeolus project deliverable D3.1. It presents a review of existing strategies for dispatching the wind farm active power setpoint to individual wind turbines. In addition to the power control strategies, the basics of model-based predictive control technology and its application to a number of industrial problems of relevance have been summarised.

With respect to the farm active power dispatch strategies, four types have been identified:

- **Proportional Distribution** in which the farm power setpoint imposed by the transmission system operator is allocated to individual turbines based on the available powers of, or wind speeds at, the turbines.
- **PI Control** in which a PI controller (with anti-windup) is used to derive the turbine power setpoints based on, e.g., the error between the farm power setpoint and its actual output.
- **Fuzzy Control** in which a fuzzy logic control based scheme is used to determine the power setpoints of individual turbines based on the errors of power and of its derivative.
- **Optimisation** in which active power dispatch is formulated as a constrained optimisation problem aimed at minimising, e.g., deviations of the generated active and reactive powers of the farm from the transmission system operator requests and others such as farm internal active power losses, the number of turbines in operation and status changes of turbines.

It is observed that:

- None of the works reviewed, except for one that is based on optimisation and two patent applications by the same inventors (for different geographical regions), takes turbine fatigue load into consideration when deriving the power SPs. The optimisation-based work does not consider fatigue load as intended by the Aeolus project. The patent applications merely propose the concept of fatigue load minimisation/distribution, without specifying how this is to be done.
- Few of these strategies address the effect of **nonlinearity** in wind farms and turbines thus it is unclear how they will perform in practice.

- All the studies reviewed, except for one, were carried out on simulation models of small farms. The **scalability** of these strategies to large farms has not been assessed.

- None of these strategies addresses the issue of **reconfigurability**.

- All controllers handle the limits on the available power at each turbine. However, except for in the optimisation based strategies, other operational **constraints** are not handled.

With respect to model-based predictive control technology, it is observed that:

- In spite of a wide range of practical applications since its inception, utilisation of the technology in the wind energy field has so far been very limited.

- In addition, existing applications in this field appear to be confined to the local control of turbines. Farm-wide power dispatch control is yet to be explored.

Nevertheless, it emerges from the studies that model-based predictive control appears to be an appealing candidate for wind farm active power supervisory control, due mainly to its capability in performing online constrained optimisation, tracking a future reference trajectory and handling multivariable processes as well as processes with long dead-times.

Nevertheless, several issues must be addressed with respect to such a supervisory control algorithm:

- **Nonlinearities** - Should a nonlinear model of the wind farm be linearised at one or more operating points and used for control design, or should a form of nonlinear model-based predictive control be used?

- **Cost Function** - How should the objectives of controlling WF power output and minimising turbine fatigue loads be integrated into a suitable cost function for control design?

- **Disturbances** - How well will the technology handle disturbances typically found in the farm?

- **Scalability** – Whilst standard MPC algorithms scale well, NMPC algorithms are less scalable. The degree of scalability depends on the type of nonlinearity and has to be assessed on a case-by-case basis.

These issues are addressed in the second part of deliverable D3.1, in a separate document, ISC_300409_Deliverable_D3.1_0002(1)_PU.pdf.

Abbreviations

DD	Delegated Dispatch
DFIG	Doubly-Fed Induction Generator
FSWF	Fixed Speed Wind Farm
FSWT	Fixed Speed Wind Turbine
GO	Grid Operator (same as Transmission System Operator)
HMPC	Hierarchical MPC
MBPC	Model-Based Predictive Control (same as MPC)
mp-MPC	multi-parametric MPC
MPC	Model Predictive Control (same as MBPC)
MHC	Moving Horizon Control (same as MPC)
NMPC	Nonlinear MPC
PCC	Point of Common Connection (of the wind turbines in the wind farm to the grid) (same as POI)
PI	Proportional Integral
RMPC	Robust MPC
POI	Point Of Interconnection (same as PCC)
RHC	Receding Horizon Control (same as MPC)
SC	Supply Chain
SCM	Supply Chain Management
SP	Setpoint
TSO	Transmission System Operator (same as Grid Operator)

VSWF	Variable Speed Wind Farm
VSWT	Variable Speed Wind Turbine
WF	Wind Farm
WFSC	Wind Farm Supervisory Control
WT	Wind Turbine
WTG	Wind Turbine Generator

Terminology

Nominal Power	(rated) maximum power that the turbine can generate continuously
Peak Power	(rated) maximum power that the turbine can generate for a specified (short) period, e.g. 1 s
Process (or plant)	the system to be controlled
Rated Power	same as (rated) nominal power, except when qualified as 'rated peak power', in which case it is the same as 'peak power' above

1. Introduction

1.1 Requirements for Large-Scale Wind Farm Level Control

The main objective of WP3 is to develop a strategy for wind farm (WF) active power supervisory control that exploits the interdependencies between wind turbines (WTs) in order to improve power performance and reduce fatigue loads.

The control strategy is required to satisfy two, often contradictory, objectives:

1. Achieve, or maximise the probability (given the random/stochastic nature of wind variations and other disturbances acting on the WTs) of achieving the farm active power setpoint (SP) as demanded by the grid operator.

2. Reduce the (extreme and fatigue) loads experienced by the WTs.

Other requirements of the control strategy include:

3. It needs to consider the effects of nonlinearities and operation constraints.

4. It must be scalable to WFs of different sizes.

In addition, since in offshore WFs it is generally only possible for maintenance and repairs to be carried out at irregular intervals, the farm control system should be able to function when some WTs (a) become unavailable due to e.g. damage or damage prevention and/or (b) have to run at reduced load in order to e.g. prevent additional wear or damage. Consequently:

5. The control system needs to be reconfigurable.

Finally:

6. The control algorithm must be sufficiently inexpensive computationally to be implemented in practice.

1.2 Objectives and Scope of Review

Compared to the extensive studies performed on individual WTs, in particular during recent years, there has been relatively little effort on the more complex control of large-scale WFs.

This report forms the first part (three parts in total) of the Aeolus project deliverable D3.1. It contains a review of existing supervisory control strategies and applications in WFs and other systems with similar control-related characteristics. The ultimate objective of this deliverable is to identify the farm control strategy to be investigated and implemented by WP3.

Note that the review is generally restricted to the dispatch control of WF active power, in line with the scope agreed by the project partners. However, a few studies on reactive power control are included in Appendix A for reference purposes.

The second part of the deliverable, which is in a separate document (ISC_300409_Deliverable_D3.1_0002(1)_PU.pdf), will present a detailed specification of the control strategy identified for the Aeolus project, including the control objectives, WT/WF model to be used, constraints, wind flow interaction, etc.

1.3 Structure of Document

This report is organised as follows:

- Section 2 – This section contains the review of existing strategies for WF active power control.
- Section 3 – This section introduces the basics of the model-based predictive control (MPC) technology and briefly examines its use in a number of industrial problems of relevance.
- Section 4 - This section contains a discussion on several issues related to WF active power control.
- Section 5 – This section contains the conclusions of the review.
- Section 6 – This section lists all literatures referenced in the report.
- Appendix A – This section includes a few studies on reactive power control.
- Appendix B – This section describes MPC applications in supply chain management systems, hydropower plant, etc., as examples of types of systems that display similarities to the WF power SP dispatch problem.

2. Wind Farm Active Power Control Strategies Review

Four types of WF active power control strategies were identified from the publications obtained during the literature review stage:

- Proportional distribution
- PI control
- Fuzzy Control
- Optimisation

These control strategies are covered in this section.

During the literature search process, a couple of patent applications were also uncovered. The two applications are on the same work by the same inventors, Schram and Vyas [75], [76], and were filed at the European and US patent offices[1], respectively. The patent applications are concerned with the concept of fatigue load minimisation/distribution. However, no proposals are presented as to what the actual approach for achieving this should be. For this reason, no further review can/will be carried out at this stage.

2.1 Proportional Distribution

The simplest strategy for dispatching the farm power SP to individual WTs is that of proportional distribution according to the (maximum) available powers of the WTs.

For example, such a strategy is used by Kaneko et al. [38] to control WFs connected to small power systems. In their approach, the power command (P_{go_i}) of the i-th WT is generated as follows:

(1) $$P_{go_i} = P_{com} \cdot \left(\frac{P_{go\_\max_i}}{\sum_{i=1}^{N} P_{go\_\max_i}} \right)$$

where:

[1] The applications were submitted between 2005 and 2006 and published during 2007.

- P_{com} is the WF power command set by the transmission system operator (TSO).

- $P_{go\_max_i}$ is the maximum available output power of the i-th WT for a given wind speed[2], approximated by the following equation (refer to Sakamoto et al. [69] for the derivation of (2) and (3)):

(2) $$P_{go\_max_i} = d_1(\beta) + d_2(\beta) V_{w_i}^2$$

where V_{w_i} is the instantaneous wind speed for the i-th WT and d_1 and d_2 are expressed as functions of the pitch angle β:

(3) $$\begin{aligned} d_1(\beta) &= \alpha_{11} + \alpha_{12}\beta + \alpha_{13}\beta^2 + \alpha_{14}\beta^3 \\ d_2(\beta) &= \alpha_{21} + \alpha_{22}\beta + \alpha_{23}\beta^2 + \alpha_{24}\beta^3 \end{aligned}$$

where $\alpha_{ij}, i = 1,2,\ j = 1,2,3,4$ are constants.

In another example, Hansen et al. [27] propose a controller for integrated power and frequency control as well as reactive power and voltage control for WFs with variable speed WTs with doubly-fed induction generator (DFIG). In this controller, the references for both active and reactive powers are distributed proportionally to the individual WTs by a **dispatch function block**. The WT active power reference is calculated as follows:

(4) $$P_{ref}^{WT_i} = \frac{P_{av}^{WT_i}}{P_{av}^{WF}} P_{out}^{wfc}$$

where:

- $P_{ref}^{WT_i}$ is the power reference signal for the i-th WT.

- P_{out}^{wfc} is the WF active power reference generated by a **Main controller** block. This block contains a PI controller with anti-windup that computes the power error and generates P_{out}^{wfc} based on P_{ref}^{wfc}. P_{ref}^{wfc} is calculated by a **Control functions** block

[2] In Kaneko et al. [38], this is described as "each WTG's output power corresponding to wind speed (0~1 pu)", which is here interpreted as the maximum available output power of the turbine for a given wind speed.

based on one or several control functions required by the TSO (balance control, delta control, power gradient limiter or automatic frequency control)).

- $P_{av}^{WF} = \sum_{i=1}^{n} P_{av}^{WT_i}$, $i = 1,...,n$, is the total available active power of the WF.
- $P_{av}^{WT_i}$ is the available active power for the i-th WT, determined by the WT based on its power curve and the estimated wind speed.
- n is the number of WTs in the farm.

In devising a DFIG farm dynamic operating reserve[3] allocation scheme (with a supervisory controller similar to those presented in de Almeida et al. [3] and Rodríguez-Amenedo et al. [66]), Chang-Chien et al. [18] use a proportional distribution strategy slightly different from those mentioned above. The WF primary reserve requested by the TSO is distributed based on the wind speed[4], instead of available power, for each WT. Specifically, the TSO farm reserve is distributed to the WTs as follows:

(1) $$P_{WT}(V_j) = P_{WF} \times DF_{WT}(V_j)$$

where:

- $P_{WT}(V_j)$ is the deloaded margin for each WT operating under V_j.
- P_{WF} is the primary reserve requested by the TSO.
- V_j is the wind speed.
- $DF_{WT}(V_j)$ is the distribution factor for each WT for a given wind speed V_j, calculated as follows:

(1) $$DF_{WT}(V_j) = \frac{W(V_j) \times n(V_j)}{\sum_i W(V_i) \times n(V_i)} \times \frac{1}{n(V_j)}$$

[3] For primary frequency control.

[4] As the deloaded margin of a WT is affected by the wind speed (the higher the wind speed, the higher the deloaded margin).

where:

- $W(V_j)$ is the weighting factor[5] for wind speed V_j.

- $n(V_j)$ is the number of WTs operating at V_j in the WF.

Clearly, a proportional distribution based strategy has the advantage of being very simple to implement. It also takes one type of constraint, the maximum available power of WTs, into consideration when setting power commands as in the cases of [27] and [38]. Unfortunately, in the process it takes no explicit account of the fatigue/stress experienced by individual WTs.

2.2 PI Control

Kristoffersen and Christiansen [40] describe the "Windfarm Main Controller" of the Horns Rev WF in Denmark. The total power SP for all WTs is the TSO-supplied power demand plus a PI-control term. The latter is based on the error between TSO demand and actual generated power. The WF total power SP is distributed to the individual turbines based on their "power capability and state". However, details of the power distribution algorithm are not described. It should be pointed out that this is the only description found during the review of an actual active power controller applied to an operational WF, as opposed to a simulation model.

Rodríguez-Amenedo et al. [67] propose a three-level control scheme for a cluster of two WFs, a fixed-speed WF (FSWF) and a variable-speed WF (VSWF), interconnected by a feeder and a common high voltage overhead line up to the point of interconnection (POI) with the transmission network through a transformer. The control objective is to meet the active and reactive power SPs from the TSO. In this scheme a PI based strategy (with anti-windup) is used to generate the active and reactive power references for the individual WTs.

The three control levels are:

- POI Controller – At the highest level of the hierarchy, this controller computes the active and reactive power errors and generates the power references for the individual WF controllers through a dispatch function block[6].

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[5] In general, the higher the wind speed, the greater the weighted value.

- Wind Farm Controllers – With the power references from the POI Controller as input, each of the WF controllers computes the active and reactive power references for the individual WT controllers in the farm.

- Wind Turbine Controllers – The WT controller has the task of achieving the WT power references set by the respective WF controller.

The WF Controllers generate WT active and reactive power references according to the technology used (i.e. fixed-speed wind turbine (FSWT) or variable-speed wind turbine (VSWT)). In the case of active power control:

- FSWF Controller – Power control is achieved through a progressive WT disconnection strategy using a PI controller with an anti-windup feature. The controller compares the WF active power reference with the measured value and derives the same power references for all FSWTs.

  The WT power reference derived is then compared with the actual power produced by each FSWT. Using a hysteresis band controller, a connection or disconnection command is sent[7] to each FSWT.

- VSWF Controller – The VSWF Controller first compares the WF active power reference with the actual power value. The error is then used by the PI controller to derive the same active power reference for each WT[8].

Note that all calculations are performed on a **per (power) unit** basis, normalised by the total rated power of the entire generation that is connected downstream of the POI.

This PI based strategy has the advantage of being simple and is easily scalable to large WFs. However, it does not take operational constraints into consideration. In addition, individual

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[6] The Dispatch Function can implement different strategies, two of which are discussed in Rodríguez-Amenedo et al.. [67]

[7] According to Rodríguez-Amenedo et al. [67], it is essential to delay the reference signal to each WT in order to avoid a complete WF shut-down, when implementing this strategy. This is necessary for it to cope with the situation when the WF power reference is low while the power generated by the WTs is high; otherwise a disconnection signal may be generated and sent to all WTs at the same time (as the same per-unit power reference is shared by all WTs in the farm).

[8] If the power reference is increased but one or more WTs already are working at the maximum capacity, the other WTs in the farm will assume the load.

WTs are treated equally in this strategy, i.e. they receive the same power reference regardless of their conditions such as (accumulated) fatigue loads.

Lubosny and Bialek [45] also use a PI-based WF supervisory control scheme. As a supplementary control loop to the existing supervisory power control, this is a power fluctuation controller dedicated to reducing WF power output variations[9] (in a few to tens of seconds) using:

(a). An external energy storage device, or

(b). A power reserve by operating some of the WTs in the farm part-loaded.

The power fluctuation supervisory controller (i.e. (b) above) includes the following components:

- WFC – The objective of this controller is to minimise the variations of the WF real power output. It acts on the WTs selected to run as part-loaded, changing their output to smooth out.
- PRC – The objective of this controller is to "set and keep value of power reserve that could be additionally fed to the grid from the selected turbine(s)".

The control scheme was simulated using a WF model with four WTs. Using the scheme, VSWTs can be controlled and operated in parallel with FSWTs[10]. The control structure is considered to be plant-independent and applicable to other types of intermittent generators including wave or solar.

However, the fatigue load issue of WTs is not considered. Indeed, as pointed out by Lubosny and Bialek [45], the effectiveness of the system is limited by the dynamics of the WTs and the use of pitch-angle control may increase the possibility of fatigue of the blade and blade-hub material.

An automatic generation control system is developed for a VSWT farm by Rodríguez-Amenedo et al. [66]. It is, however, unclear how the active power error is used in the supervisory controller (i.e. WFAPC) to generate the power references for the WTs.

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[9] The scheme is said to be of use also for "system-wide controls that are related to power variation, such as frequency control or damping of power swings".

[10] Of which the ability to minimize power fluctuations is said to be limited to filtering by their rotor inertia.

2.3 Fuzzy Control

Costa et al. [20] propose a WF supervisory control scheme based on a fuzzy logic controller. The fuzzy logic controller has the errors of power and of its derivative as inputs. Its output, derived from a set of nine rules, is used to determine the individual WT power references.

The method by which these WT power references are determined is not given. In addition, the scheme does not consider constraints and fatigue of WTs.

Although, in principle, fuzzy control has the capability of handling nonlinear systems, it is difficult to assess the performance to be expected of the strategy since this performance depends on what those nonlinearities are.

The above control scheme is demonstrated in simulation on a set of three WTs only. In terms of scalability and computational efficiency, it is anticipated that, in general, fuzzy control based strategies may score fairly well comparing with model predictive control, although not as good as the 'equal per-unit' PI control discussed before.

2.4 Optimisation

Optimisation based strategies have also been used for WF active power dispatch.

For example, de Almeida et al. [3] describe such a strategy for active and reactive powers in a DFIG WF, taking into consideration farm internal losses and wind resource availability. The farm controller uses an optimisation algorithm to determine the active and reactive power SPs for each WT that operates over a deloaded maximum power extraction curve[11] in order to meet the overall farm output requirement. The objective is to minimise the difference between the total active and reactive powers delivered by the WF and those required by the TSO. The WT controller achieves the required SPs by adjusting the rotor speed through pitch control and control of the static converter[12].

The following two optimisation scenarios are considered:

1. Minimising deviations of WF active and reactive output powers from the TSO requests;

[11] "to provide some primary frequency capability response".

[12] Implementation of this control in the DFIGs requires the presence of a secondary active power control loop.

2. Minimising:

   – Deviations of WF active and reactive powers from the TSO requests, and

   – Active power losses[13] within the WF

The optimisation problems are formulated as the minimisation of a quadratic cost function (refer to Figure 1 of de Almeida et al. [3] for the corresponding WF configuration):

(5) $$Min\left\{ p_1(P_d - P_{total})^2 + p_2(Q_d - Q_{total})^2 + p_3\left[(P_{out_1} - P_d)^2 + \sum_{i=2}^{n}(P_{out_i} - P_{S_{i-1}})^2 \right] \right\}$$

subject to:

(6) $P_{out_i}(V,\theta) = P_{in_i}(V,\theta) + P_{S_i}(V,\theta)$

(7) $Q_{out_i}(V,\theta) = Q_{in_i}(V,\theta) + Q_{S_i}(V,\theta)$

(8) $P_{inj_i} = P'_{inj_i}(V,\theta)$

(9) $Q_{inj_i} = Q'_{inj_i}(V,\theta)$

(10) $P_{\min_i} \le P_{inj_i} \le P_{o_i}$ (WT active power generation limits)

(11) $Q_i^m \le Q_{inj_i} \le Q_i^M$ (WT reactive power generation limits)

(12) $V_i^m \le V_i \le V_i^M$ (voltage control limits imposed to buses according to relay settings)

(13) $\theta^m \le \theta_i \le \theta^M$ (limits of bus phase angles, assumed in [-π, π] in the optimisation)

$i = 1, 2, \ldots n$

where:

[13] In the transformers and lines inside the WF.

- n is the number of WTs in the WF.

- p_1, p_2 and p_3 are weighting factors that represent and are used to adjust the influence of each term of the cost function.

- P_d and Q_d are, respectively, the total active and reactive power outputs of the WF.

- P_{total} and Q_{total} are the active and reactive output powers requested by the TSO, respectively.

- P_{out}, P_{in}, P_S and $P_{inj}^{'}$ are vectors representing the active powers flowing in the branches of the WF.

- P_{inj} and Q_{inj} are vectors of which elements represent the active and reactive powers injected by WTs into the grid, i.e. the active and reactive power SPs of the WTs. These are the outputs of the optimisation algorithm, the decision variables.

- P_{oi} represents the maximum active power, or available power, that can be generated by the i-th WT (which depends on the available wind power and a pre-defined active power curve adopted by the corresponding DFIG active power control loop).

- $P_{\min i}$ is the minimum deloaded active powers of the i-th WT and $P_{\min i} = (1 - \frac{\%_{deloading}}{100})P_{oi}$.

  A turbine that operates in the deloaded condition has a SP within the range between minimum and maximum of the power extraction curves for a given wind speed (Chang-Chien [18]; also refer to Figure 4 of de Almeida et al. [4]).

- Q_{out}, Q_{in}, Q_S and $Q_{inj}^{'}$ are vectors representing the reactive powers flowing in the branches of the WF.

- V is a vector of the voltages of the network nodes.

- θ is a vector of the phase angles of the network nodes.

- Q_i^m and Q_i^M represent the reactive power generation limits.

- V_i^m and V_i^M represent the voltage control limits imposed on all buses.

- θ^m and θ^M represent the bus angle limits.

The above optimisation problem is solved for P_{inj} and Q_{inj} using a so-called "primal-dual predictor corrector interior point algorithm" described in Bemporad [7].

It is however unclear from the description in de Almeida et al. [4] as to how the above optimisation variables P_{inj} and Q_{inj} (i.e. the outputs of the optimisation algorithm) are actually used in the DFIG control loops.

The effectiveness of the above approach is illustrated in de Almeida et al. [3] using a small WF connected to an infinite bus bar.

Comparing with the MPC strategy (see Section 3), the above method is similar in that:

- It is an optimisation based strategy.

- It uses a quadratic cost function.

- It is able to cope with constraints.

- It is model-based (e.g. P_{Si} and P_{outi} will need to be estimated using models as they are not measured).

However, it is different in that:

- It does not use the concept of "receding horizon" (ref. Section 3.1.1). Instead, it seems to be an instantaneous optimisation (i.e. looking at the current time-step only, not at the future) solved using the primal-dual predictor corrector interior point algorithm.

The method is studied in the context of a small WF thus its computational feasibility in and scalability to large WFs remain unclear (although in general it can be said that the scalability of this type of optimisation tends to be poor).

The above work is extended further by Castronuovo et al. [17] to a higher level, delegated dispatch (DD)[14], with the objective of optimising the output while complying with the TSO requirements. The extended control considers the current and forecasted productions of the WTs, the state of the system, the prices obtained by each generator in the market and different levels of output restriction. WFs are classified into three types according to their controllability as shown in Table 1.

Table 1. WF controllability classification by Castronuovo et al. [17]

WF Type	Controllability	
	Active Power Output	**Production Power Factor[15]**
1	✓[16]	✓[17]
2	×	✓
3	×	×[18]

The DD optimisation problem is formulated as follows:

[14] A DD is "a control centre that transmits the requirements of the system operator in critical situations to distributed generation resources, by monitoring and controlling the wind generation producers in a region", i.e. a midpoint between the TSO and the individual WFs (usually of smaller sizes) under control [17]. The work described in [17] considers all WFs that are connected to the same transmission network bus and interconnected by a subtransmission grid as belonging to the same DD.

[15] The power factor of an AC electric power system is defined as the ratio of the real power (P - the capacity of the circuit for performing work in a particular time) flowing to the load to the apparent power (S - the product of the current and voltage of the circuit), and is a number between 0 and 1. The apparent power S can be greater than the real power P due to energy stored in the load and returned to the source, or due to a non-linear load that distorts the wave shape of the current drawn from the source. More information is available in http://en.wikipedia.org/wiki/Power_factor.

[16] Between the maximum instantaneous availability and zero

[17] Between specified limits

[18] All Type 3 generators are considered to have the same specified power factor in the same hour in this study, although the actual value can be different for different period of the day as specified by the TSO [17].

(14) $$Max\left\{\sum_{j=1}^{m} c_j \cdot S_{Gj} \cdot \cos\varphi_j - \sum_{j=1}^{m2+m3} \mathrm{fnp} \cdot c_j \cdot (S_{Gj} \cdot \cos\varphi_j - P_{Gj}^{av})^2 - \sum_{j=1}^{m3} \mathrm{fnc} \cdot c_j \cdot (\varphi_j - \varphi_f)^2\right\}$$

subject to:

(15) $$P_{out} \leq P_{out}^{Max}$$

(16) $$S_{Gi}\cos\varphi_i - P_{Di} - P_i(V,\alpha) = 0$$

(17) $$S_{Gi}\sin\varphi_i - Q_{Di} - Q_i(V,\alpha) = 0$$

(18) $$\alpha_{sk} = 0$$

(19) $$0 \leq S_{Gi}\cos\varphi_i \leq P_{Gi}^{av}$$

(20) $$\cos\varphi_i \geq \cos\varphi_i^{\min}$$

(21) $$V_i^{\min} \leq V_i \leq V_i^{\max}$$

(22) $$-T_{ij}^{\max} \leq T_{ij} \leq T_{ij}^{\max},\ i \neq j$$

(23) $$\varphi_f = \begin{cases} \cos^{-1}(\mathrm{fpf}) & \text{for capacitive fpf} \\ -\cos^{-1}(\mathrm{fpf}) & \text{for inductive fpf} \end{cases}$$

i=1,…,n

where:

- c_j is the price obtained by the i-th WT for active power production.
- S_{Gi} and φ_i are the values of apparent power and power factor angles at the i-th bus.
- m is the number of plants controlled by the DD.
- m_2 and m_3 are the numbers of Types 2 and 3 WFs, respectively.
- n is the number of buses of the internal system.

- fnp and fnc are the weighting coefficients for maintaining the active power generation of Types 2 and 3 and the power factor for Type 3, respectively.
- φ_f is the expected power angle in Type 3 buses.
- P_{Di} and Q_{Di} are the active and reactive power demands at the i-th bus, respectively.
- $P_i(V,\alpha)$ and $Q_i(V,\alpha)$ are the calculated values of the active and reactive powers at the i-th bus, respectively (obtained from the power flows in the transmission lines linked to the bus).
- V_i and α_i are the module and angle of the buses voltages at the i-th bus, respectively.
- α_{sk} is the voltage angle at the slack bus.
- P_{Gi}^{av} is the maximum forecasted production of the i-th WT in the considered period.
- P_{out} and P_{out}^{Max} are, respectively, the total output and maximum total output of the active power production in the internal area.
- $V_i^{\min}$ and $V_i^{\max}$ are the minimum and maximum limits of the voltage module in the i-th bus.
- $T_{ij}^{\max}$ is the maximum transmission limit of the apparent power in the line between the i-th and j-th buses, respectively.
- fpf is the specified power factor in Type 3 buses.

Again, the optimisation is solved using the predictor-corrector primal-dual interior point algorithm. Taking into consideration of the economic interest of the producers, the output restrictions set by the TSO and the WF controllability, it obtains the best active and reactive productions of the WFs and the state of the internal system (or, where no operational solution is found, suggests possible corrective solutions[19]).

---

[19] Examples of such corrective solutions are reductions in the active power productions of WFs of Types 2 and 3 and specified values for the power factor production in Type 3 WTs.

Moyano and Peças Lopes [48] use an optimisation based WF control strategy to define the commitment of WTs and their active and reactive power SPs. For a given request from the WF dispatch centre[20], it derives the active and reactive power SPs of the individual WTs based on short-term wind power forecasts (i.e. power availability). Some of the issues addressed include, for a given time horizon:

- Minimising the connection/disconnection of WTs.
- Restricting the limits for the WT reactive power generation.

The solution is obtained by solving the following two interrelated optimisation problems:

- Unit commitment (to determine WT schedule).
- Wind farm dispatch (to determine WT SPs).

With the objective of minimising the number of WTs in operation and status changes[21] for a given time horizon, the **unit commitment** problem[22] is formulated as follows:

(24) $$Min\sum_{i=1}^{np}\sum_{j=1}^{ng}(b_j^i X_j^i + c_j^i Y_j^i + d_j^i Z_j^i + \psi P_{ND_u}^i + \psi P_{ND_L}^i)$$

subject to:

(25) $$-\sum_{j=1}^{ng} X_j^i P_{g_j}^{MaxS^i} + \sum_{k=1}^{nb} P_{d_k}^i + P_{Loss}^i - P_{ND_u}^i \leq 0 \text{ for } i = 1,\ldots,np$$

(26) $$\sum_{j=1}^{ng} X_j^i P_{g_j}^{MinS^i} - \sum_{k=1}^{nb} P_{d_k}^i - P_{Loss}^i - P_{ND_L}^i \leq 0 \text{ for } i = 1,\ldots,np$$

(27) $$(X_j^i - X_j^{i-1}) - Y_j^i \leq 0 \text{ for } i = 2,\ldots,np$$

(28) $$-Y_j^i \leq 0 \text{ for } i = 2,\ldots,np$$

---

[20] Which controls several WFs.

[21] To reduce maintenance cost for WTs and switching devices

[22] A mixed integer linear programming optimisation problem

(29) $(X_j^{i+1} - X_j^i) - Z_j^i \leq 0$ for $i = 1,...,np-1$

(30) $-Z_j^i \leq 0$ for $i = 1,...,np-1$

(31) $-P_{ND_u}^i \leq 0$ for $i = 1,...,np$

(32) $-P_{ND_L}^i \leq 0$ for $i = 1,...,np$

where:

- b_j^i, c_j^i and d_j^i are the operational costs associated with maintaining the turbine activity and the cost of startup and shutdown for the j-th WT at the i-th period.
- n_p and n_g are the total numbers of periods and WTs, respectively.
- X_j^i, Y_j^i and Z_j^i are binary variables representing, respectively, the (on/off) status, startup and shutdown of the j-th WT in the i-th period.
- $P_{ND_u}^i$ (≥0) and $P_{ND_L}^i$ (≥0) (and the coefficient Ψ) are introduced to avoid the infeasibility in the unit commitment problem when:

  (a). The load is greater than the generation capability for the i-th period[23], or

  (b). The load is less than the generation capability for the i-th period[24].

- $P_{g_j}^{MaxS^i}$ and $P_{g_j}^{MinS^i}$ are, respectively, the maximum available active power limit[25] and the minimum technical limit[26] of the j-th WT at the i-th period.

---

[23] The maximum total active power generated is less than that which is requested by the TSO plus the internal losses in the WF for the period.

[24] The minimum total active power generated is greater than that which is requested by the TSO plus the internal losses in the WF for the period.

[25] Determined from the wind power forecasting for the WT at the i-th period (as derived using the approach described in [57])

[26] If there is enough wind speed to keep the WT in operation

- $P_{d_k}^i$ is the active power required by the dispatch centre at the k-th interconnection bus at the i-th period[28].

- $P_{g_j}^i$ is the active power generated by the j-th WT at the i-th period.

- P_{Loss}^i is an estimate of the WF internal losses at the i-th period.

To obtain the active and reactive outputs (SPs) of the scheduled WTs as determined by solving the above unit commitment problem, the following **WF dispatch** problem[27] is formulated. It aims to minimise the mismatch between the total WF generation output (active and reactive) and dispatch centre requests for each period taking operational constraints into consideration:

$$(33) \qquad Min \ \ \sigma_P^i \alpha_P^i + \sigma_Q^i \alpha_Q^i$$

subject to:

$$(34) \qquad (1-\alpha_P^i)P_{d_k}^i - P_{g_k}^i + P_k^i(V_k^i, \theta_k^i) = 0 \ \text{for} \ k = 1,2,...,nb$$

$$(35) \qquad (1-\alpha_Q^i)Q_{d_k}^i - Q_{g_k}^i + Q_k^i(V_k^i, \theta_k^i) = 0 \ \text{for} \ k = 1,2,...,nb$$

$$(36) \qquad 0 \le \alpha_P^i \le 1$$

$$(37) \qquad 0 \le \alpha_Q^i \le 1$$

$$(38) \qquad P_{g_j}^{MinS^i} \le P_{g_j}^i \le P_{g_j}^{MaxS^i} \ \text{for} \ j \ = 1,2,...ng$$

$$(39) \qquad Q_{g_j}^i \le \left| \sqrt{\left(\frac{3L_{m_j}\left|V_j^i\right|}{2L_{s_j}} \left|i_{r_j}^i\right| \right)^2 - \left(P_{g_j}^i\right)^2} \right| - \frac{3\left|V_j^i\right|^2}{4\pi f_s L_{s_j}} \ \text{for} \ j = 1,2,...,ng$$

$$(40) \qquad -Q_{g_j}^i \le \left| \sqrt{\left(\frac{3L_{m_j}\left|V_j^i\right|}{2L_{s_j}} \left|i_{r_j}^i\right| \right)^2 - \left(P_{g_j}^i\right)^2} \right| + \frac{3\left|V_j^i\right|^2}{4\pi f_s L_{s_j}} \ \text{for} \ j = 1,2,...,ng$$

---

[27] A non-linear optimisation problem

(41) $V_k^{Min} \le V_k^i \le V_k^{Max}$ for $k = 1, 2, ...nb$

where:

- α_P^i and α_Q^i represent the percentages of the non-delivered active and reactive power outputs at the i-th period, respectively.
- σ_P^i and σ_Q^i are the weightings used to control the priorities of active and reactive power generation at the i-th period, respectively.
- $P_{d_k}^i$ and $Q_{d_k}^i$ represent the WF active and reactive powers required by the dispatch centre at the k-th interconnection bus for the i-th period[28], respectively.
- $P_{g_j}^i$ and $Q_{g_j}^i$ represent the active and reactive power outputs to be generated by the j-th WT at the i-th period, respectively.
- V_k^i is the voltage module at the k-th bus of the WF at period i.
- V_k^{Max} and V_k^{Min} (both constant) are the maximum and minimum voltage modules at bus k, respectively.
- $P_k^i(V_k^i, \theta_k^i)$ and $Q_k^i(V_k^i, \theta_k^i)$ are the active and reactive power flow equations for bus k at period i, respectively.
- θ_k^i is the voltage angle at bus k, period i.

The above problem is also solved using the predictor-corrector version of the Primal-Dual Non-Linear Interior Points method presented in Bemporad et al. [7].

In general, optimisation of the above type has poor scalability when it comes to large WFs (of exponential, polynomial or similar relation with system size). Nevertheless the above is said to be suitable for large WFs. This is, however, not demonstrated by Moyano and Peças Lopes [48]; instead, a relatively small, hypothetical WF (with 10 WTs and 21 lines forming

[28] $P_{d_k}^i = 0$ and $Q_{d_k}^i = 0$ if k is not an interconnection bus.

two feeders connected to the grid interconnection bus through a transformer) is used for illustration.

Finally, the unit commitment optimisation takes into consideration the maintenance cost for WTs and switching devices due to startup and shutdown operations and status changes. However, a constant cost is assigned when a turbine is on. In other words, costs do not vary with power level, turbulence effect on rotors, etc. The issue of WT fatigue load is therefore not addressed in the way proposed by the Aeolus project.

2.5 Miscellaneous

Javid et al. [37] address the operation and control of an array, or a cluster[29], of WTs in utility systems. A hierarchical strategy for farm-level control is used in closed-loop operation (which is one of three proposed WT operation/control regimes[30]) where WT power output variations are reduced via blade pitch control.

In this strategy, the WF power SP control is carried out by a so-called Coordinated Cluster Controller where the total generation from the WT cluster tracks an SP (which is determined by a so-called Area Array Controller to reduce the variations in the total generation of all the WTs in the system) based on the following:

- If the cluster power SP is less than its open-loop power[31], then each WT SP is selected such that the difference between the controlled pitch angle and the open-loop pitch angle is the same for all WTs in the cluster (Equal Blade Pitch Margin). It is however not stated as to how this pitch angle difference is determined.

[29] In the paper, the term array and cluster are used interchangeably to describe a group of wind turbines. In this sense, an array or cluster of wind turbines can perhaps be interpreted as any of the following: a wind farm, a set of wind turbines within a farm or even a set of wind turbines anywhere (although perhaps impractical) so long as they are aggregated into the same group for the purpose of power control by the same controller.

[30] The other two operation/regimes are open-loop (where WTs are controlled to the extract maximum power from the wind up to the unit rating) and feedforward (where WT generation is measured and compensated for by conventional generation units).

[31] The open-loop power obtainable (i.e. maximum power from the wind up to the unit rating) is calculated based on the measured actual power and blade pitch angle from each WT.

- Otherwise (i.e. if the cluster power SP is greater than or equal to its open-loop power), the WT SP is selected such that the controlled pitch angle and the open-loop pitch angle are the same for all WTs in the cluster[32].

Although the above work is concerned with arrays/clusters of WTs, the functions of the Coordinated Cluster Controller are clearly relevant to farm-level supervisory control considered in the Aeolus project. The higher level Area Array Controller may also be relevant[33].

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[32] Note this is not explicitly stated in [37]. but interpreted here.

[33] For instance, WTs in a WF can be divided into one or more subgroups of WTs with each subgroup being controlled by a Coordinated Cluster Controller and the control of the subgroups (i.e. management of the Coordinated Cluster Controller) performed by an Area Array Controller.

3. Model Predictive Control Application Review

Model Predictive Control (MPC)[34], or Model-Based Predictive Control (MBPC), refers to a class of advanced control algorithms that calculate control signals that optimise, according to certain predefined criteria, the performance of a process over a predefined future time horizon. The calculations are based on a model of the process.

Various linear and nonlinear MPC algorithms have been developed since the 1970s. Qin and Badgwell [63]) summarises the different strands of the linear MPC algorithms developed between 1970s and 2000s, including:

- IDCOM, IDCOM-M and SMCA
- DMC, QDMC and DMC+
- Connoisseur
- SMOC
- HIECON
- PFC
- PCT, RMPC and RMPCT

A collection of earlier research work on nonlinear MPC (infinite, quasi-infinite and receding horizon) can be found in Allgöwer and Zheng [3]. A more recent overview of nonlinear MPC and applications can be found in Qin and Badgwell [62].

In spite of its applications in various industries (e.g. refining, petrochemicals, chemicals, food processing, automotive and aerospace), MPC has yet to be applied to the WF supervisory control problem. This section introduces the basics of this technology and briefly examines its use in a number of industrial problems of relevance to wind farm control.

[34] Also known as Receding Horizon Control (RHC) or Moving Horizon Control (MHC).

3.1 Model Predictive Control Basics

3.1.1 Basic Ideas

MPC calculates the values of the manipulated variables (i.e. the controller outputs) over a predefined number of future[35] steps[36] (N_u, called control horizon), based on the behaviour of the process over a predefined time horizon in the future (N_p, called the prediction horizon, defined by a start time N_1 and an end time N_2; that is, $N_p = N_2 - N_1$). The forecast or prediction of the process behaviour is obtained using a process model.

In general, an MPC algorithm has the following elements (Pike et al. [56]):

- A predictor equation - Based on the process model, this is used to estimate future system outputs based on the current and past system inputs and outputs.
- A reference trajectory - This defines the desired closed-loop behaviour[37]. Although not often mentioned, the effects of known future disturbances can be treated in a similar way as future reference trajectories.
- A cost function – This is to be minimised through selection of the manipulated variables.

Both the process model and the cost function can take different mathematical forms, leading to different forms of MPC (e.g. DMC, GPC).

An idea essential to this type of algorithm is that of receding horizon control. At any sampling instant, although a sequence[38] of the manipulated variables is computed over the control horizon to minimise the cost function, only the first instant of the computed sequence is applied to the plant. The computation process is repeated at the next sampling instant with the new information that becomes available. Although the computational

[35] From current time (step/sample)

[36] Since MPC is almost invariably treated in discrete time, elapsed time is usually expressed in a number of samples or steps rather than in seconds.

[37] Note in addition to a reference trajectory, this may also be expressed in several other forms such as a setpoint, zone, or funnel as summarised by Qin and Badgwell [63].

[38] That is N_p steps into the future

demand of an optimisation algorithm running and terminating at every control update is generally prohibitive, online (approximate) solution of the optimal control problem by the receding horizon control makes MPC feasible for many practical applications. In addition, receding horizon control offers a number of advantages including (Kwon and Han [42]):

- Handle input and state constraints.
- Good tracking performance.
- Applicable to a wide range of systems (e.g. time-delayed or nonlinear systems).

3.1.2 Process Model

Process models may be derived exclusively from test data, first principles (physics) or a mixture of both. Typical process models used include finite impulse/step response, polynomial (e.g. CARMA/CARIMA/Box-Jenkins) and state-space models. Although practical processes are inherently nonlinear, until recently the great majority of practical MPC applications have been based on linear dynamic models, due to a number of factors (Qin and Badgwell [62]):

- Linear models (e.g. step and impulse response models) are relatively easy to understand and identify from process data.
- For most regulator problems, the accuracy of carefully identified linear models is in many cases sufficient (in the neighbourhood of the operating point).
- Reliable solution algorithms and software can be found easily for the MPC with a linear model and quadratic cost function.

On the other hand, nonlinear models may offer better behaviour forecasts for nonlinear systems, in particular for those "processes that operate over large regions of the state space – semi-batch reactors, frequent product grade changes, processes subject to large disturbances" (Rawlings [64]).

Clearly model accuracy and computational efficiency remain critical issues to be considered and balanced in practical applications when it comes to selecting appropriate MPC strategies (linear or nonlinear) since:

- The performance of MPC is affected by the accuracy of the process model used.

- Nonlinear MPC (NMPC) algorithms are significantly more complex than the linear MPC algorithms.

A review of computationally efficient approaches to NMPC can be found in Cannon [15]. Further discussions are given in Section 3.1.6 on MPC performance as well as MPC strategies that are specifically designed for robustness.

3.1.3 Cost Function

The cost function is formulated to allow a trade-off between minimising future errors and control actions (i.e. reducing actuator movements), and is usually in a quadratic form.

An example cost function for a SISO plant is:

$$J(t)=\sum_{j=N_1}^{N_2}\left[SP(t+j)-CV(t+j)\right]^2+\sum_{j=1}^{N_u}\left[\lambda MV(t+j-1)\right]^2 \qquad (42)$$

where:

- t is the current time step.
- SP is the process setpoint.
- CV is the controlled variable (i.e. the process output to be controlled).
- MV is the manipulated variable (i.e. process input or controller output).
- N_2 - N_1 is the prediction horizon (in number of samples).
- N_u is the control horizon.
- λ is the control weighting to be adjusted to trade-off a small output error against limited control action.

As can be seen from the above, it is a prerequisite for MPC to know about SP changes.

A more complex and general example of the cost function is from the MATLAB Model Predictive Control Toolbox (Bemporad et al. [7]). This cost function is applicable to multivariable plant and includes disturbances:

$$\min_{\Delta u(k|k),\ldots,\Delta u(m-1+k|k),\varepsilon}\left\{\sum_{i=0}^{p-1}\left(\sum_{j=1}^{n_y}\left|w_{i+1,j}^{y}\left(y_j(k+i+1|k)-r_j(k+i+1)\right)\right|^2+\sum_{j=1}^{n_u}\left|w_{i,j}^{\Delta u}\Delta u_j(k+i|k)\right|^2+\sum_{j=1}^{n_u}\left|w_{i,j}^{u}(u_j(k+i|k)-u_{j\mathrm{target}}(k+i))\right|^2\right)+\rho_\varepsilon\varepsilon^2\right\} \qquad (43)$$

where:

- p is the maximum of the prediction horizon (or, strictly speaking, the prediction end time) and the control horizon;
- n_y is the number of controlled process outputs;
- n_u is the number of controller outputs;
- "$( )_j$" denotes the j-th component of a vector;
- "(k+i|k)" denotes the value predicted for time k+i based on the information available at time k;
- r(k) is the current sample of the output reference, subject to[39]:

$$
\begin{aligned}
& u_{j\min}(i)-\varepsilon V^{u}_{j\min}(i)\le u_j(k+i\,|\,k)\le u_{j\max}(i)+\varepsilon V^{u}_{j\max}(i)\\
& \Delta u_{j\min}(i)-\varepsilon V^{\Delta u}_{j\min}(i)\le \Delta u_j(k+i\,|\,k)\le \Delta u_{j\max}(i)+\varepsilon V^{\Delta u}_{j\max}(i)\\
& y_{j\min}(i)-\varepsilon V^{y}_{j\min}(i)\le y_j(k+i+1\,|\,k)\le y_{j\max}(i)+\varepsilon V^{y}_{j\max}(i)\\
& i=0,\dots,p-1\\
& \Delta u(k+h\,|\,k)=0,\ h=m,\dots,p-1\\
& \varepsilon\ge 0
\end{aligned}
\tag{44}
$$

with respect to {Δu(k|k),…, Δu(m-1+k|k)} (input increments) and ε, and by setting u(k) = u(k-1) + Δu(k|k)*, where Δu(k|k)* is the first element of the optimal sequence.

- $w^{\Delta u}_{i,j}$, $w^{u}_{i,j}$ and $w^{y}_{i,j}$ are non-negative weights for Δu, u and y, respectively. The smaller a weight is, the less important the behaviour of the corresponding variable is to the overall performance index.
- $u_{j\min}, u_{j\max}, \Delta u_{j\min}, \Delta u_{j\max}, y_{j\min}$ and $y_{j\max}$ are the lower and upper bounds on u, Δu and y, respectively.
- ε (≥0) is the slack variable.

[39] The constraints on u, Δu, and y are relaxed by introducing the slack variable.

- ρ_ε is the weight on ε which penalizes the violation of the constraints. The larger it is in relation to the input and output weights, the more penalized the constraint violation is.

- $V^u_{j\min}, V^u_{j\max}, V^{\Delta u}_{j\min}, V^{\Delta u}_{j\max}, V^y_{j\min}$ and $V^y_{j\max}$ are the so-called Equal Concern for the Relaxation (ECR) vectors which contain non-negative values[40] representing the concern for relaxing the corresponding constraint[41].

- $u_{target(k+i)}$ is a SP for the input vector, typically used when the number of inputs is greater than that of outputs.

The MATLAB Model Predictive Control Toolbox also supports the following alternative quadratic cost function:

$$
\begin{aligned}
(45)\quad J(\Delta u,\varepsilon) &= \sum_{i=0}^{p-1}[y(k+i+1|k)-r(k+i+1)]^T Q[y(k+i+1|k)-r(k+i+1)] \\
&+\Delta u(k+i|k)^T R_{\Delta u}\Delta u(k+i|k)+[u(k+i|k)-u_{\text{target}}(k+i)]^T R_u[u(k+i|k)-u_{\text{target}}(k+i)]+\rho_\varepsilon \varepsilon^2
\end{aligned}
$$

where:

- Q and R_u are, respectively, n_y x n_y and n_u x n_u positive semi-definite matrices.

3.1.4 Tuning Parameters

The following is a summary of the tuning parameters of MPC algorithms together with some of the recommended general settings for practical applications (Bemporad et al. [7], Pike et al. [56]):

- Start of the prediction horizon N_1 – This is normally set to be the same as the (smallest) process dead-time (the time after which a change in controller output has an effect on the process output), in number of samples.

- End of the prediction horizon N_2 – This is usually set to be no greater than the settling time of the process[42].

---

[40] ECRs can be time varying.

[41] The larger it is, the softer the constraint. V=0 represents a hard constraint that cannot be violated.

[42] To capture the dominant process dynamics.

- Control horizon N_u – This should normally be chosen to reflect a relatively small control horizon, e.g., 3 - 5.

- Weighting λ - The cost function weighting.

- Sampling period – This can be set as a fifth of the dominant time constant (in general it must be fast enough to represent the process dynamics of interest but not so fast to make the computation too expensive to implement).

3.1.5 Operational Constraints

Another distinctive feature of MPC is its ability to integrate operational constraints into the optimisation process[43]. Various types of constraints[44] on process outputs and inputs (the manipulated variables) can be introduced into MPC. Typically, constraints on the process outputs are related to product quality. Constraints on the process inputs may be due to factors such as (Maciejowski [46]):

- Actuator saturation, e.g. values with a finite range of adjustment, non-negative flow rates with maximum values due to fixed pipe diameters or control surfaces with limited deflection angles (e.g. pitch blade angles).

- Limits on rates of change of actuator signals e.g. valves and other actuators with limited slew rates.

In general, unlike the unconstrained problem, no analytic solution exists for the constrained version except in certain special cases (Pike et al. [56]).

The ability to consider constraints in the optimisation process is beneficial in practice for several reasons (Maciejowski [46]):

- The controlled process has the potential to run most profitably. This is because MPC can potentially control the underlying process to run at or, more likely, near[45]

[43] This does not make it less applicable to unconstrained problems.

[44] These include (Qin and Badgwell [63]): hard constraints (those which must never be violated), soft constraints (those which may be violated but the violation is penalised in the cost function) and setpoint approximation constraints (where deviations above and below the constraint are penalised)

[45] Because in reality some reserve (i.e. away from the constraints) may have to be made in order to account for unexpected process disturbances.

constraints, potentially the most profitable points of operation for many applications.

- MPC enables more natural handling or formulation of certain process control problems[46].
- MPC eliminates the need for integral wind-up removal if the actuator constraints are included as controller output constraints in the design.

3.1.6 Performance and Robustness

Abu-Ayyad and Dubay [2] compare the performance of several MPC algorithms, including Dynamic Matrix Control (λ-DMC), shifted DMC (m-DMC), extended predictive control (EPC), simplified predictive control (SPC) and generalised predictive control (GPC). Comparisons are made using two examples, DC motor speed control (with a relatively fast sampling time of 10 ms) and steel cylinder temperature control (with a relatively slow sampling time of 5 s), and on the basis of the conditionality of the system matrix, DC gain of the controller, integral absolute error index and closed-loop specification. For the examples studied, all of the considered algorithms were found to offer good disturbance rejection and effective tracking of reference trajectories, with fast settling times and minimal overshoot, albeit of varying degrees.

The accuracy of process models used in MPC affects the control performance. For example, it is known for plant-model mismatch (i.e. the difference between the plant and the model, also referred to as model uncertainty) to lead to sluggish, overly conservative or unstable control performance (Wang and Rawlings [84]).

Various robust MPC (RMPC) methods have been proposed in which the plant-model mismatch[47] is taken into consideration explicitly when determining the optimal control actions, to guarantee stability and setpoint tracking. A typical RMPC method, for example, will use a set of models (as opposed to one as in the traditional MPC) to predict the system behaviour and determine the corresponding optimal control actions using a min-max

[46] For example, the problem of controlling the level of a buffer tank to be within a minimum and maximum limits is more naturally expressed as a constraint on the tank level ("zone objective") than as meeting a defined setpoint (Maciejowski [46]).

[47] Although its impact is lessened by the feedback in MPC (as in other forms of feedback control), this mismatch is not explicitly accounted for in the traditional MPC.

optimisation which seeks to minimize the largest deviation of the set of predicted behaviour from the desired. For more information, reviews of the developments in RMPC can be found in Bemporad and Morari [9] and Jajali and Nadimi [33].

3.1.7 Advantages and Disadvantages

In summary, MPC offers the following advantages:

- It can be used to control difficult processes, particularly those with long dead-times.
- Known future reference signals are utilised.
- Known process disturbances can be compensated for.
- It can be extended to multivariable problems naturally.
- Process operational constraints can be incorporated.

Its disadvantages include:

- A good process model is necessary.
- It can be computationally expensive as optimisation is solved on-line.
- System properties such as stability and robustness are more difficult to analyse due to repeated computation of controls.

The key issues in the successful application of the MPC strategy include:

- Problem formulation – This involves defining an appropriate cost function structure, selecting the tuning parameters (such as N_u, N_1, N_2 and λ), and identifying the relevant process constraints, if any.
- Process model – This involves defining a process model that is suitable for the problem at hand and offers the appropriate level of prediction accuracy.

3.1.8 Applications

Utilisation of MPC in the wind energy field has so far been very limited, in spite of a wide range of practical applications since 1970s, notably in (among others) the process industry (e.g. [9], [13], [20], [22], [47], [54], [59] , [62] and [82]) and power industry (e.g. [24],

[25], [26], [28], [30], [31], [32], [41], [44], [52], [55] and [87]). Furthermore, existing applications in the wind energy field have been confined to WT local control (see e.g. [12], [29], [43], [69], [74] and [88]). MPC based farm-level power control has yet to be explored.

It is not intended for this report to provide a survey into all these existing studies due to the following observations:

- The great majority of these studies deal with problems that have a different nature from that of the Aeolus project.

- A disproportional amount of work would be required to cover the vast volume of published works in any general review.

- Review papers on MPC already exist, see for example Jalali and Nadimi [33], Kouvaritakis et al. [39] and Qin and Badgwell [62] and [63].

As examples of types of systems that display similarities to the WF power SP distribution problem, Appendix A lists applications of MPC to supply chain management systems and hydropower plant.

3.2 Hierarchical MPC

It is possible in MPC for conflicting (multiple) control objectives and constraints to exist where a solution becomes infeasible. This is one area where the method of hierarchical MPC (HMPC) (e.g. Baskar et al [5], Iino et al. [33][34], Negenborn et al. [50], Scattolini and Colaneri [72]) is considered to help. In HMPC, a higher level of control is introduced to resolve such conflicts. Running at a slower time scale, the higher-level controller coordinates the lower-level controllers. Taking into considerations of the interactions among the multiple subsystems, it can modify, where necessary, the objectives and constraints in order to obtain feasible solutions. Running at a faster time scale, on the other hand, the lower-level controllers concentrate on solving more concrete control problems.

The idea of HMPC has been applied to cement raw material mixing control (Iino et al. [33] [34]) and voltage stability of power networks (Negenborn et al. [50]). Please refer to Appendix B.3 for more information. HMPC is also proposed by Baskar et al [5] for use in an Intelligent Vehicles based traffic management system.

3.3 Multi-Parametric MPC

In comparison with the traditional form of MPC discussed in Section 3.1, multi-parametric MPC (mp-MPC) is a control strategy developed to overcome the implementation problems associated with the traditional MPC (in particular computationally expensive online optimisation).

The idea of mp-MPC and a review of recent developments on industrial and experimental applications are given by Dua et al. [23]. In mp-MPC, the process of solving optimisation online is transformed into two stages:

- **Offline parametric optimisation**[48] - This derives a complete map of look-up functions that relates the controller output to the state, together with the critical regions in state space where each of the look-up functions is valid.
- **Online function selection and evaluation** - At every sampling instant, this obtains the corresponding controller output (process input) from the look-up function map as follows:
  - Get the current measurements of state.
  - Find the critical region in which the state belongs.
  - Obtain the corresponding function in this region.
  - Evaluate the function for the given state measurements to derive the controller output.
  - Apply the controller output to the system.

Comparing with solving optimisation at every control update (as in the traditional MPC), the above online process is computationally more economical to be implemented on a range of hardware platforms (from e.g. PLCs already installed in a plant infrastructure to micro-controller boards and small flash memory chips).

The target application areas of mp-MPC are systems with fast dynamics or fast sampling time or where the hardware selection is governed by the controller cost and size, including (Dua et al. [23]):

[48] Where the sequence of future control inputs is the optimisation variable and the initial condition is the parameter.

- Automotive - e.g. catalytic converters, traction systems, active valve trains
- Aerospace and defence - e.g. guidance, navigation and formation control of unmanned vehicles
- Industrial - e.g. robotics, process control
- Biomedical - e.g. artificial organs, drug delivery and anaesthesia systems

Application of mp-MPC control is demonstrated through several examples including a pilot plant reactor, an air separation unit (constrained by limited size of controller hardware), an active valve train (AVT) car engine (constrained by limited size of controller hardware and fast sampling time) and a blood glucose control system (constrained by fast sampling time) in Dua et al. [23]. It is shown that mp-MPC demonstrates "similar if not better behaviour and advanced benefits (for example for the AVT system) than PID".

To summarise, the advantages of mp-MPC include:

- Comparing with traditional MPC – It can be applied to application with faster dynamics or restricted hardware size.
- Comparing with PID – It can incorporate operational and/or physical constraints and optimise systems behaviour (as in traditional MPC).

More details on the technique and applications can be found in a number of publications, including Bemporad et al. [8], Pistikopoulos et al. [58], [59] and Sakizlis et al. [70].

4. Discussions

4.1 Nonlinearities

WF systems are nonlinear, and therefore WF models are usually nonlinear as well. Nonlinearities in WF models could potentially affect their suitability for supervisory control by MPC. A WF model is usually nonlinear due to nonlinearities in both the individual WTs and their interactions. For example, Jauch [36] lists the following nonlinearities of WT systems:

1. Blade aerodynamic properties
2. Constraints on pitch angle SP imposed by minimum (zero) and maximum/rated power limits
3. Pitch rate limits
4. Dynamic stall effect

To handle these nonlinearities, the nonlinear model can be linearised (at multiple operating points) and used for control design, or a form of NMPC can be used. The former (multiple-model MPC) is simpler in terms of the number of calculations per time step, and therefore runs faster. However, the control performance depends on the combination of the variations in process dynamics with the operating points and the number of operating points used for linearisation as well as the switching mechanism used. If many points are used and the dynamics vary little between points, the performance will be good; if few points are used and the dynamics vary significantly between points, the performance will be poor. Mechanisms for switching between the models/controllers must also be considered carefully to avoid instability.

On the other hand, 'full' NMPC as a general area is still in a research or experimental stage. The type of nonlinear control required to handle nonlinear aspects of a system depends on the type of nonlinearity. Therefore, some form of customisation is needed to handle most types of nonlinearity.

An exception to this general rule is the issue of constraints. Most current commercial MPC tools, such as the MATLAB MPC Toolbox (Bemporad et al. [7]) include the handling of (fixed) constraints on controller and process outputs as a standard feature. Typically, both controller and process output constraints are handled by means of (penalty) cost functions, although controller output constraints can sometimes be treated as hard constraints (not to be violated at all).

Another issue that must be taken into consideration in selecting the appropriate MPC strategy is computational efficiency since NMPC algorithms are significantly more complex than MPC based on linear models.

Finally, it is worth mentioning that, at the farm level, the wind flow can probably (depending on the outcome of WP2) be described as a combination of dead-time and other dynamics. The dead-time component of the wind flow from one turbine to another downwind is long (several seconds) compared with the process time constants (or dynamics) of the turbines themselves. In this respect an MPC-based WF control strategy would be beneficial.

4.2 Control System Implementation Issues

The algorithms to implement MPC can vary from relatively simple, for single-model linear MPC, to very complex. Most of the development and testing of WF control strategies in Aeolus will take place in a simulation environment. In these conditions, the complexity and execution time of the WF control algorithm are not severely limiting factors in its use or assessment.

However, two of the tasks in the work programme involve the evaluation of the controller in real-time operation (T3.5) and its implementation and testing on a (ECN) test farm (T1.5). Therefore, at least a version of each WF control strategy to be evaluated on the test farm will have to run on the test-farm control system.

Some of the limiting factors for the implementation on industrial control systems are:

- **Memory (RAM) required** – Typically, industrial systems have less memory than modern office/laboratory computer systems.
- **Array (vector/matrix) dimensions** – In most modern control design environments, such as MATLAB, array dimensions can be calculated or changed on-line easily. However, in industrial systems array dimensions often have to be specified and fixed in advance of running the main program. This makes it impossible to calculate these dimensions on-line as functions of other parameters.

- **Execution time taken per function evaluation** - This depends on the complexity of the function. For example, a square-root calculation takes more time than a summation of two numbers.

- **Number of function evaluations per (sample) time step** – The number of function evaluations and the execution time per evaluation together (in combination with other factors such as data I/O time, which are largely unaffected by the controller algorithms) determine the total execution time per sample (or time step). For real-time operation, this total execution time has to be smaller than the controller sample time.

- **Availability of standard functions in controller** - For example, some control systems may have built-in PID algorithms in their standard programming language while some others may not even have a square-root function built-in.

- **Ability to include C modules** - Some control systems can include C modules. If that is the case at the ECN test farm, C-code can (probably) be generated directly from MATLAB/Simulink through the Real-Time Workshop. Only the interface to the main WF control program would need to be programmed manually.

Detailed information, in the form of control system manuals, etc., is required from ECN to enable the assessment of the (memory, type of functions, etc.) limitations imposed by the WF control system on the WF control strategy and algorithm. If the WF controller for the full-size test farm is too large or too slow to run, a version with a reduced number of WTs could be considered. Such a decision would be taken in discussion with the Aeolus partners.

4.3 Disturbances

Various types of disturbances can be found in a WF. Examples include:

1. Stochastic disturbances
   - Wind (magnitude and direction, flow both to WF and within WF among the WTs). This includes both sudden gusts and more gradual changes.
   - Sudden breakdowns of WTs.
   - Reductions of WT power due to wear and tear.
2. Deterministic disturbances

- Planned shutdowns or start-ups of WTs.
- Planned reductions of WT power (to prevent damage or excessive wear).

Consequently, the capability of a chosen WF supervisory control strategy (MPC or other) in coping with these farm disturbances should be assessed.

4.4 Fatigue Loads

The project partners decided that, within the Aeolus project, the WF control will be focused on minimising fatigue loads of operational WTs, excluding loads caused by e.g. start-up and shutdown operations. Within this context, there exist a number of influencing factors on the WT fatigue load such as:

- Power generation required
- Wind conditions (e.g. turbulence caused by neighbouring turbines)
- Controller design

It remains a key issue for WP3 WF control design to express and integrate the WT fatigue loads into a suitable cost function to reflect the objectives of controlling WF power output and minimising the fatigue loads.

None of the works reviewed in Section 2 on WF control, except for Moyano and Peças Lopes [48] and Schram and Vyas [75], [76], explicitly take WT fatigue load into consideration when deriving WT power SPs.

Although touched upon in their optimisation-based strategy (see Section 2.4), Moyano and Peças Lopes have not considered WT fatigue load in the way proposed by the Aeolus project. In their approach, the costs for switching on and off are considered in the unit commitment problem (i.e. optimise which WTs should run at any particular time). A constant cost is assigned when a turbine is on. In other words, the costs are assumed not to vary with power level, turbulence effect on rotors, etc., in contrast to the Aeolus approach.

Schram and Vyas' patent applications (see Section 2) deal with the concept of fatigue load minimisation/distribution, but do not go into any detail about how this is proposed to be done.

4.5 Reactive Power Control

In the optimisation-based WF control strategies reviewed in Section 2.4, reactive power is considered together with active power in the control algorithm in deriving the corresponding control SPs. However, for simplicity of both the WFSC strategy and the models required to simulate the WF, Aeolus will restrict itself to control of active power only.

5. Conclusions

This report has presented a review of existing strategies for dispatching the farm active power SP to individual WTs. Four distinctive approaches to power SP dispatch were identified:

- **Proportional Distribution** - In this strategy, the farm power SP is allocated to individual WTs according to e.g. the available powers of, or wind speed at, the WTs. It has the advantage of being very simple to implement but takes no account for the fatigue loads experienced by WTs in the distribution.

- **PI Control** - In this strategy, a PI controller (with anti-windup) is used to derive the WT power SPs based on e.g. the error between the TSO-imposed farm power SP and the actual power output of the farm. It is generally simple and scalable to large WFs. Nevertheless, operational constraints are not taken into consideration in the process nor are WT conditions such as fatigue loads. This is the only active power control strategy that is recorded as actually being applied to a wind farm (the Horns Rev WF in Denmark, see Kristoffersen and Christiansen [40]).

- **Fuzzy Control** - In this strategy, a certain fuzzy logic control based scheme is used to determine the WT power SPs based on the errors of the farm's power and its derivative. In terms of scalability and computational efficiency, it is anticipated that in general fuzzy control based strategies may score fairly well comparing with MPC, although not as good as the PI control. Again, constraints and fatigue of WTs are not considered. It is also difficult to assess the performance to be expected of the strategy with respect to nonlinear systems since, although fuzzy control in principle has the capability of handling nonlinear systems, how well it can perform depends on what those nonlinearities are and how well the controller is tailored to the nonlinearities.

- **Optimisation** - In this strategy, the active power dispatch problem is formulated as a constrained (instantaneous) optimisation problem with the objective of minimising e.g. deviations of the generated active and reactive powers of the farm from the TSO requests and others, such as farm internal active power losses, the number of WTs in operation and status changes. Examples of operational constraints considered are active and reactive power generation limits, voltage control and bus phase angle limits. A farm model is generally needed in these optimisation-based strategies for the purpose of estimating some of the variables that are not measured in practice. Since the existing studies of constrained optimisation are in the context of small WFs, its computational feasibility in and scalability to large WFs remain unclear. In general, the scalability of this type of optimisation tends to be poor.

In summary, it can be observed that:

- None of the works reviewed, except for Moyano and Peças Lopes [48] and Schram and Vyas [75], [76], take WT fatigue load into consideration when deriving WT power SPs. Moyano and Peças Lopes' optimisation based strategy does not consider fatigue load in the way intended by the Aeolus project. Schram and Vyas's patent applications merely propose the concept of fatigue load minimisation/distribution, without specifying how it is to be done.

- Few of the strategies address the effect of **nonlinearity** in WF and WT. Thus, it is unclear how these strategies will perform when implemented in practice.

- With the exception of the PI strategy described by Kristoffersen and Christiansen [40], all the studies reviewed have been carried out on simulation models of small sized WFs. Therefore, there is no conclusive evidence of their effectiveness and **scalability** to large WFs. However, based on the general characteristics of the control strategies it can be stated that:

    - Proportional distribution and PI control are well scalable.

    - Optimisation methods are poorly scalable (complexity and number of calculations tend to increase exponentially with the process dimensions).

    - Fuzzy control itself scales fairly well, although not as well as proportional distribution and PI control. However, its tuning can be difficult and time-consuming for large systems.

- None of these strategies addresses the issue of **reconfigurability**.

- Except for in the optimisation based strategies, operational **constraints** are not handled.

In addition to the above farm power control strategies, the basics of the MPC technology and its application to a number of industrial problems have been summarised. It has been observed that, in spite of a wide range of practical applications since 1970s, notably in (among others) the process and power industries, utilisation of the technology in the wind energy field has been very limited. Further, existing applications in this field appear to have been confined to WT local control. MPC-based farm power control is yet to be explored.

However, it also emerges from the reviews that MPC is indeed a suitably appealing strategy for use by Aeolus as a WFSC strategy, due mainly to its capability in performing online constrained optimisation, tracking a future reference trajectory and handling multivariable processes as well as processes with long dead-times.

Nevertheless, several key issues must be addressed when developing an MPC-based WFSC algorithm, including:

- Nonlinearities in WF model – Should the nonlinear model be linearised and used for control design or a form of NMPC be used?
- Cost function – How should the objectives of controlling WF power output and minimising WT fatigue loads be expressed uniformly and integrated into a suitable cost function for control design?
- Disturbances – How well will MPC cope with disturbances typically found in a WF?
- Scalability – Standard MPC algorithms scale well; they are used in refineries and other large systems with several hundreds of I/O variables. NMPC algorithms are less scalable; the degree of scalability depends on the type of nonlinearity and has to be assessed on a case-by-case basis.

These issues are addressed in the second part of deliverable D3.1, in a separate document, ISC_300409_Deliverable_D3.1_0002(1)_PU.pdf.

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Appendix A. Reactive Power Control Strategies

As seen from the discussions in section 2, some of the strategies reviewed (e.g. proportional distribution in Hansen et al. [27] and PI control in Rodríguez-Amenedo et al. [66]) have been used separately for reactive power control. In others, e.g. the optimisation based strategies in de Almeida et al. [3], Castronuovo et al. [17] and Moyano and Peças Lopes [48], reactive power is considered with active power in the control algorithm in deriving the corresponding control SPs.

Besides the above, several other studies with the focus on WF reactive power control were encountered during the literature search. Although reactive power control is outside the scope of the project, these studies are briefly discussed below for reference.

Proportional distribution and PI strategies have been developed for reactive power control in DFIG WFs:

- **Proportional Distribution** (Saenz et al. [68], Tapia et al. [80] and [81]) – This algorithm spreads the required farm reactive power proportionally among all operative generators. Given the farm reactive power reference Q_{REF}, the reactive power SP Q_{Si} for the i-th WT is calculated as follows:

$$Q_{S_i} = Q_{REF} \frac{Q_{S_i \max}}{\sum_{j=1}^{n} Q_{S_j \max}} \tag{46}$$

  where n is the number of operative WTs and Q_{Simax} is the maximum reactive power that can be generated by the i-th WT[49].

- **PI Control** (Tapia et al. [80] and [81]) - Instead of the reactive power SP, the PI algorithm (with anti-windup) calculates the power factor reference SP φ_{REF} of the WT as follows:

[49] Obtained from the measured active power generated by the WT and P/Q limits.

$$
(47)\quad
\begin{aligned}
&\varphi_{REF0}(k) = \varphi_{REF}(k-1) + k_p(1+\frac{T_s}{2T_i})e_\varphi(k) + k_p(\frac{T_s}{2T_i}-1)e_\varphi(k-1)\\
&\varphi_{REF}(k) = \begin{cases} \varphi_{REFMin}, & \text{if } \varphi_{REF0}(k) < \varphi_{REFMin} \\ \varphi_{REFMax}, & \text{if } \varphi_{REF0}(k) > \varphi_{REFMax} \\ \varphi_{REF0}(k), & \text{if } \varphi_{REFMin} \le \varphi_{REF0}(k) \le \varphi_{REFMax} \end{cases}
\end{aligned}
$$

where:

- T_s is the sampling period.
- k_p and T_i are the proportional and integral time constants of the PI controller, respectively.
- e_φ is the error between the desired (φ_{REF}) and measured actual power factor (φ_{FARM}) of the farm, i.e.:

$$
(48)\quad e_\varphi = \varphi_{REF} - \varphi_{FARM}
$$

Assuming the actual active power generated by the farm (P_s) is maintained at the optimum value and only the reactive power Q_s changes to follow the power factor SP, then:

$$
(49)\quad
\begin{aligned}
\varphi_{REF} &= \arctan\frac{Q_{SREF}}{P_S}\\
\varphi_g &= \arctan\frac{Q_{SFARM}}{P_S}
\end{aligned}
$$

Once $\varphi_{REF}(k)$ is calculated, it is sent to the individual WT local control systems to derive the stator-side reactive power references as follows:

$$
(50)\quad Q_{SREF_i}(k) = [P_{SREF_i}(k) + P_{ri}(k)]\tan[\varphi_{REF}(k)] - Q_{ri}(k)
$$

where:

- P_{SREF_i} is the stator-side active power reference for the i-th DFIG.

- P_{ri} and Q_{ri} are the rotor-side active and reactive powers generated/absorbed by the i-th DFIG, respectively.

According to Tapia et al. [81], the proportional distribution algorithm is considered impractical for many farms operating in Spain due to the high computational needs involved and the sensitivity of the system performance in sudden changes of wind speed. However, it is not made clear which calculations in the algorithm cause these "high computational needs". The proportional distribution algorithm is simple compared to most other distribution algorithms listed in this review.

Although the PI algorithm is reported to be more robust than the proportional distribution algorithm, it gives only one common power factor reference to all WTs in the farm, regardless of the wind conditions/distribution over the farm and the fatigue loads of the WTs. The power factor of a WT will only differ from the reference value if it reaches its minimum or maximum power factor limit.

Appendix B. Relevant MPC Applications

The review of control strategies that are suitable for WF supervisory control included a survey of the control strategies that are commonly used in applications with similar characteristics. One of these areas is supply chain management (SCM), which shares the following characteristics with WF control:

- Distribution of 'power' over several 'generators' (in SCM supply of total customer demand from a variety of manufacturing sites and/or storage depots).
- Significant stochastic disturbances (in SCM customer demand, vs. wind in WFs).

One clear difference is that the WF only has one 'customer' for its power, the grid operator. However, since this represents a simplification of the WFSC problem relative to SCM, it would not preclude the use of SCM control methods in WFs.

B.1 MPC for Supply Chain Management

B.1.1 Problem

A supply chain (SC) consists of multiple layers/echelons[50] of nodes (customers, retailers, distributors, manufacturers and suppliers) interlinked together to transform raw materials to intermediate and/or finished products and to distribute the finished products to the end customers[51].

An essential problem in SCM is to maximize profit through balancing product availability (customer satisfaction) and inventory level (costs) in the various layers of the SC. An SC is generally driven by customer orders placed with retailers. For example, at the top layer, a key issue in providing a good level of customer satisfaction lies in maintaining product availability, which in turn means keeping an appropriate level of replacement orders with suppliers: too many leads to increased storage and inventory holding costs, while too few compromises customer satisfaction level. This act of balancing customer satisfaction and costs is repeated in the distribution and plant levels of the SC.

---

[50] An echelon in a supply chain refers to a "distinct generic procedure as part of the production/distribution process" (Riddalls et al. [65]).

[51] A more abstract definition of a supply chain is given by Riddalls et al. [65] as "a system of business enterprises

Optimal SCM has become increasingly complex due to factors such as changes in customer preferences, rising manufacturing and production costs, globalisation and increasing competition (Sarimveis et al. [71]). The SCM problem is characterized by the following:

- Inventory optimisation to ensure critical levels of customer service are maintained at an acceptable cost;
- Uncertain dynamic system, variations in product demands and raw material supplies, lead time and reliability of service as well as commodity prices and costs;
- Disturbances such as machine breakdowns;
- Forward flow of materials and backward flow of information;
- Demand amplification (the so-called "bullwhip" phenomenon, where small fluctuations in demand at the retailer end are amplified as they travel through the SC).

The following statement by Chen et al. [19] serves to clarify the problem[52]:

Given:

- Manufacture data (e.g. batch manufacturing quantity of regular time and overtime, overtime number constraint), transportation data (e.g. lead time, transport capacity), inventory data (e.g. inventory capacity, safe inventory quantity), cost parameters (e.g. manufacturing, inventory), buyers' and providers' acceptable levels for product prices and forecasted product demands with known probabilities.

Determine:

- Production plan of each plant, transportation plan of each distribution centre, sales quantity and compromised product price of each participant, inventory level of each enterprise and all costs involved, with the objective of integrating the multi-echelon decisions simultaneously to:
  - Guarantee a fair profit distribution among all participants;

that link together to satisfy consumer demand".

[52] Which may be expressed differently by different researchers/practitioners.

- Increase, as much as possible, the customer service, safe inventory and product-prices satisfaction levels and robustness of all considered objectives (to product demand uncertainties).

Various types of mathematical methods have been used to model and analyse SCs including (Riddalls et al. [65]):

- Continuous-time differential equation models
- Discrete-time difference equation models
- Discrete-event simulation models
- Operational research techniques

Since the 1950s, control theory has been applied to design efficient SCM strategies based on dynamic simulation models of supply chains. A comprehensive review of the application of both classical and advanced control methods can be found in Ortega and Lin [53] and Sarimveis et al. [71].

In the following, several examples of applying MPC to multi-product, multi-echelon SC network management are described.

B.1.2 Applications

Through three benchmark cases, Wang et al. [83] examine the application of MPC to SCM in the semiconductor manufacturing sector. The problem is characterised by a highly stochastic nature and nonlinearity in throughput times, yields and customer demands.

Based on a linear deterministic model, Wang et al. formulate the semiconductor manufacturing management problem under study as follows:

$$(1) \qquad \min_{\Delta C(k|k)\ldots\Delta C(k+m-1|k)} \begin{bmatrix} \sum_{\ell=1}^{p} Q_e(\ell)\left(\hat{I}(k+\ell\,|\,k) - r(k+\ell)\right)^2 \\ +\sum_{\ell=1}^{m} Q_{\Delta C}(\ell)\left(\Delta C(k+\ell-1\,|\,k)\right)^2 \\ +\sum_{\ell=1}^{m} Q_C(\ell)\left(C(k+\ell-1\,|\,k) - C_{\text{target}}(k+\ell-1\,|\,k)\right)^2 \end{bmatrix}$$

subject to:

(2) $C_j^{\min} \le C_j(k) \le C_j^{\max}, \quad j \in \{F/T1, A/T2, F/P\}$ (limits on MVs, i.e. factory starts)

(3) $\Delta C_j^{\min} \le \Delta C_j(k) \le \Delta C_j^{\max}, \quad j \in \{F/T1, A/T2, F/P\}$ (MV rate of change limits)

(4) $I_i^{\min} \le I_i(k) \le I_i^{\max}, \quad i \in \{ADI, SFGI, CW\}$ (limits on CVs, i.e. inventory levels)

(5) $0 \le WIP_j(k) \le Cap^{\max}, \quad j \in \{F/T1, A/T2, F/P\}$ (limits on CVs, i.e. work-in-progress)

where:

- Q_e, $Q_{\Delta C}$ and Q_C are weightings.
- m and p are control and prediction horizons, respectively.
- F/T1 stands for Fab/Test1.
- A/T2 stands for Assembly/Test2.
- F/P stands for Finish/Pack.
- ADI stands for Assembly-Die Inventory.
- SFGI stands for Semi-Finished Goods Inventory.
- CW stands for components warehouse.
- WIP stands for work-in-progress.
- C_j, $C_j^{\min}$ and $C_j^{\max}$ are the start of the j-th factory and the corresponding low and high limits.
- ΔC_j, $\Delta C_j^{\min}$ and $\Delta C_j^{\max}$ are the start variation of the j-th factory and the corresponding low and high limits.
- I_i, $I_i^{\min}$ and $I_i^{\max}$ are the inventory levels in ADI, SFGI and CW and the corresponding low and high limits.
- $Cap^{\max}$ is the maximum capacity.

- $\hat{I}$ is the estimated inventory level.

The three terms of the cost function correspond to:

- SP tracking for maintaining inventory levels at externally set targets
- Move suppression for penalising changes in the starts
- Input target for keeping the starts close to daily (or per shift) target values (based on the weekly targets calculated at the strategic level)

The effects of tuning, model parameters, and capacity are demonstrated through comparing system robustness and multiple performance metrics for the cases studied. It is concluded that "a properly designed MPC controller, despite relying on a linear deterministic model, can track targets generated from inventory planning modules while improving customer service levels in environments of high stochasticity and nonlinearity in the manufacturing processes". Different performance requirements (e.g. maintaining high customer service levels and achieving tight control of inventories) can be accommodated through appropriate choice of tuning parameters. Desirable levels of performance and robustness are achieved in the case studies involving single and multiple products through proper selection of move suppression, controller model parameters, etc.

Braun et al. [14] describe an MPC strategy for a six-node (two-product, three-echelon) SC consisting of interconnected assembly/test, warehouse, and retailer entities.

Instead of one central MPC, the strategy consists of three MPC controllers, each of which handles the decisions for one echelon, passing forecasted information between the corresponding upstream and downstream nodes. The ability of the strategy to handle demand forecast error, capacity constraints, shipping and release, and plant-model mismatch is demonstrated.

Yıldırım et al. [86] also investigate a stochastic multiperiod production planning and sourcing problem involving a manufacturer with a number of plants and/or subcontractors, each of which has a different production cost, capacity, and lead time. The manufacturer needs to make decisions in order to meet the demand for different products (which is random in each period) according to the service level requirements set by its customers.

Such decisions include how much, when and where to produce, and how much inventory to carry[53].

An MPC-based approach is used, which involves solving a deterministic mathematical problem at each time period on a rolling horizon basis. Randomness in demand and related probabilistic service level constraints are integrated as additional linear constraints.

The cost function for this Stochastic Production Planning and Sourcing Problem (SP) is defined to minimize the total expected cost[54]:

(6) $$Z^* = \mathrm{Min}E\left[\sum_{t=1}^{T}\left(h_t(I_t)^+ + \sum_{i=1}^{N} c_{i,t}X_{i,t}\right)\right]$$

subject to:

(7) $I_t = I_{t-1} + \sum_{i=1}^{N} X_{i,t} - d_t,\ t = 1,\ \ldots,\ T$ (inventory balance)

(8) $P\{I_t \geq 0\} \geq \alpha_t,\ t = 1,\ \ldots,\ T$ (probabilistic service level constraints[55])

(9) $X_{i,t} \geq 0,\ i = 1,\ \ldots,\ N,\ t = 1,\ \ldots,\ T$ (production quantities cannot be negative)

where:

- Z^* is the total expected cost.
- I_t is the inventory level at the end of time period t.
- $(I_t)^+ = \mathrm{Max}\{0, I_t\},\ t = 1,\ \ldots,\ T$.

---

[53] Inventories translate to higher production and storage costs while ease the effects of disturbances and fluctuations in product demand [73].

[54] This cost is the expected value of the sum of the inventory holding and production costs in the planning horizon.

[55] This constraint reflects a Modified Type 1 Service Level requirement, which forces the probability (P{.}) of having no stock out to be greater than or equal to the given service level requirement in each period. Type 1 Service Level is frequently used and defined to be the fraction of periods in which there is no stock out. It measures whether or not a backorder occurs but is not concerned with the size of the backorder.

- d_t is the demand for a specific product at time t.
- h_t is the inventory holding cost per unit per unit time.
- T is the number of periods in the planning horizon.
- $X_{i,t}$ is the production quantity at the i-th production source at time t.
- $c_{i,t}$ is the production cost at the i-th production source at time t.
- N is the number of products.
- P{.} denotes probability.
- α_t represents the service level requirement in period t.

The above is then transformed into a deterministic equivalent problem (DEP) for approximate solution:

$$(10) \qquad Z^* = \mathrm{Min} \sum_{t=1}^{T} \left(h_t (I_0 + \sum_{\tau=1}^{t} \sum_{i=1}^{N} X_{i,\tau}) + \sum_{i=1}^{N} c_{i,t} X_{i,t} \right)$$

subject to:

$$(11) \qquad \sum_{\tau=1}^{t} \sum_{i=1}^{N} X_{i,\tau} + I_0 \ge l_t, \; t = 1, \; ..., \; T$$

$$(12) \qquad X_{i,t} \ge 0, \; i = 1, \; ..., \; N, \; t = 1, \; ..., \; T$$

where:

- l_t is the (deterministic equivalent) minimum cumulative production quantity in period t which is calculated by solving the following probabilistic inequality:
- $P\left\{ \sum_{\tau=1}^{t} d_\tau \le l_t \right\} = \alpha_t, \;$ for $l_t (t = 1, ..., T)$

Seferlis and Giannelos [73] apply a two-layered control strategy for multi-product, multi-echelon SC networks with independent production lines. This strategy involves the use of multivariable MPC to optimize the entire SC network and dedicated feedback controllers (of the PID form) to maintain safe inventory levels for each of the product and storage nodes in the network.

The MPC aims to maximize customer satisfaction (meeting customer orders) with the least operating cost over a specified rolling time horizon through adjusting variables such as transportation loads and product inventory. The rate of change in the transported quantities through the network is penalized. The individual PID controllers are embedded within the optimisation framework as additional equality constraints.

It is concluded that the proposed strategy can handle realistically sized SCs that are under a variety of stochastic and deterministic demand variations. It performs better on systems with large transportation delays and stochastic demand variation when compared with single-layered control systems.

Bei et al. [6] describe the application of an MPC strategy to determine the optimal decision variables for maximizing profit in dairy SCs. For the example problem investigated, their studies show that the MPC-based strategy excels over static optimisation, with profits and customer service levels more than doubled, due to its ability to foresee potential demand changes and accordingly balance the distribution network and the plant to coordinate resources and reduce total cost.

B.2 MPC for Hydropower Plant Production Planning and Analysis

Pursimo et al. [61] present an optimal feedback control of a hydropower plant chain[56]. The objective is to meet a predefined power demand (i.e. producing coordinated share of total controlling power demand) while simultaneously maintaining sufficient control capabilities (i.e. freedom for unexpected changes in power demand when constraints are taken into account).

The control is based on a linear state-space model of the form $x(k+1)=Ax(k)+Bu(k)$ which is an approximation of the physical properties of the river system. The ability to respond to unexpected future power changes is achieved by not operating at or near operational constraints (e.g. reservoir level bounds, discharges constraints). A quadratic cost function is used to balance the errors in both reservoir levels (deviation from the corresponding reference values) and power output (deviation from power demand).

[56] Hydraulically connected hydropower plants in a river bed, where the distances between the plants differ from a few to tens of kilometres.

It is concluded that the method is suitable for production planning and analysis of the hydro system behaviour and can also be used for on-line scheduling.

B.3 Applications of Hierarchical MPC

Negenborn et al. [50] propose a supervisory hybrid MPC strategy for voltage stability of power networks[57]. Sitting at a higher layer of control, the MPC controller provides inputs and set-points (voltage references for the Automatic Voltage Regulators and amount of load to shed) to the lower-layer primary controllers[58] based on the predicted behavior from a model featuring hybrid dynamics of the loads and the generation system. While the lower-layer controllers act directly on the actuators of the physical system and are thus faster, the MPC controller oversees and supervises the lower-layer, local controllers and is slower.

The objectives of the MPC are:

- To maintain the voltages in a range (0.9 to 1.1 p.u.) close to nominal values.
- To achieve a steady-state point of operation while minimizing switching of the control inputs

Assuming small variations[59] around an operating point, a discrete-time model of the network is obtained by linearsing the continuous differential-algebraic equations around the operating point:

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + F \\ v(k) &= Cx(k) + Du(k) + G \end{aligned} \tag{13}$$

where x, u and v represent the state variables, system inputs and bus voltage magnitudes, respectively.

The cost function is of the following form

$$J(x(k), u(k-1), U(k)) = \sum_{\ell=0}^{N-1} S(k+\ell \mid k) \tag{14}$$

[57] With components such as generators, loads, capacitor bank and transmission lines.

[58] Such that negative effects due to voltage instability after disturbances are minimized

[59] Otherwise, piecewise affine or similar models would be necessary.

where, for the IEEE 9-bus Anderson-Farmer network example used in their study (ref. Figure 1 in Negenborn et al. [50]):

- $U(k) = [u^T(k), \ldots, u^T(k+N-1)]$ represents the sequence of control inputs.
- $S(k) = \| Q_t t(k) \|_\infty + \| Q_{\Delta u} \Delta u(k) \|_\infty$.
- $Q_t = \mathrm{diag}(q_{t1}, \ldots, q_{t9})$ and $Q_{\Delta u} = \mathrm{diag}(q_{\Delta u1}, \ldots, q_{\Delta u9})$ are the diagonal penalty matrices.
- $\Delta u(k) = u(k) - u(k-1) = [\Delta r^T(k), \Delta s^T(k)]^T$ represent the variation of the manipulated variables.
- $v_1, \ldots, v_9$ represent the voltages (which must be in the range of 0.9 and 1.1 pu).
- $t_j,\ j = 1, \ldots, 9$ are the auxiliary variables that represent the upper bounds on the amounts of voltage violation, defined by:

  $$\begin{cases} 0.9 - v_j(k) \le t_j(k) \\ -1.1 + v_j(k) \le t_j(k) \quad \text{(input constraints)} \\ 0 \le t_j(k) \end{cases}$$

The control action at each time instant is obtained by minimising the above cost function[60] over the sequence of control inputs subject to the input constraints. To reduce computational complexity, the load shedding control is computed only for the first prediction step and maintained constant throughout the prediction horizon. The first step of the optimal sequence is applied to the physical network after rounding the Automatic Voltage Regulator references to the nearest feasible value. The procedure is repeated at the next sampling instant.

Iino et al. [33] propose a hierarchical MPC method to control a cement raw material mixing process. The control system configuration has three layers:

- Upper layer MPC – This calculates set points. It is formulated as a Linear Programming problem (linear cost function and constraints). The economically

[60] This is a mixed-integer linear programming problem with a linear objective function, linear equality and inequality constraints, and both continuous and discrete decision variables.

optimal operation point for each material is calculated as the ultimate ideal set point (of the next layer).

- Intermediate layer – This layer is for material mixing rate feedback control. It is formulated as a Quadratic Programming type MPC controller (quadratic cost function and linear constraints). It aims to minimize the errors in tracking material composition reference and optimal mixing ratio, as well as rapid changing of the mixing ratio.

- Lower layer DCS local control – This executes the feed rate control action corresponding to the setpoint.

Good control performance is said to have been observed from test operations at an actual plant.

Scattolini and Colaneri [72] present an approach to design a stable, two-layer hierarchical MPC. The upper layer computes the desired control variables and the maximum discrepancy allowed (i.e. "robustness bound") between the desired control variables and the implementable control action to guarantee stability and performances. This maximum discrepancy is used by the lower layer as a robustness constraint in the MPC computation. Where a solution is found, the requirements from the upper layer are considered to be fulfilled. Otherwise, the upper layer is notified, in which case a switching procedure is implemented to achieve the closed-loop properties. The MPC design procedure is considered to be general by Scattolini and Colaneri.