A Strategy for Reliability-Based Multidisciplinary Design Optimization of Wind Turbine Using BLISS and PMA

S. A. Mousavi and Fairuz I. Romli

***Abstract*—Performance of wind turbines can be negatively affected by uncertainties. Uncertainty-based multi-disciplinary design optimization (UMDO) techniques have been successfully applied in the aerospace industry and given the similarities to wind turbine design problem, application of UMDO techniques is an opportunity to improve wind turbine design. However, the major challenges of UMDO, namely computational complexity and organizational complexity caused by both time-consuming disciplinary analysis models and UMDO algorithms, still greatly hamper its usage in wind engineering. In recent years, there is a surge of research aiming at solving these problems. The purpose of this paper is to review these approaches and with the gathered information, a strategy with bi-level integrated system synthesis (BLISS) and performance measurement approach (PMA) for a reliability-based multidisciplinary design optimization of a wind turbine is proposed.**

***Index Terms*—Bi-level integrated system synthesis, performance measurement approach, sequential optimization and reliability evaluation, uncertainty-based multi-disciplinary design optimization.**

I. Introduction

In the last few years, the demands for complex engineering systems like wind turbine to have better performance, higher reliability and robustness, and lower cost and risks are on the rise. To address these competing objectives, engineers usually take design and optimization methods with consideration of all relevant aspects of the project lifecycle from the mission definition to the final disposal. All through the lifecycle, there inherently exists a vast quantity of uncertainties arising from the system itself, as well as the environmental and operational conditions that it is involved in. For instance, for a structural design, the underlying uncertainties include prediction errors induced by the design model assumptions and simplification, performance uncertainty arising from material properties and manufacturing tolerance, and uncertainties of load conditions applied on the structure during operation. These uncertainties may cause the system performance to change or fluctuate, or in some extreme cases even causes severe deviation that leads to functional fault and mission failure of the system. As Yao and *et al*. [1] described in their literature, it is thus important to consider uncertainties from the beginning of the system design process, especially the complex ones.

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In general, there are two primary categories of uncertainty-based design methods: robust design optimization (RDO) and reliability-based design optimization (RBDO). Both of these two non-deterministic approaches can also be formulated into a single design problem to concurrently seek improvements in both the system's robustness and reliability (RBRDO). RDO is a method to optimize the system design such that it will be insensitive to various variations while RBDO is a method to optimize the system design to ensure its reliability with small chance of failure under predefined acceptable level. Recently, some multi-disciplinary design optimization (MDO) methods have been extended to account for uncertainty (UMDO). Hu *et al.* [2] consider new approximation assisted multi-objective collaborative robust optimization (AA-McRO) under interval uncertainty. The new AA-McRO enhances the convergence by transforming multi-objective system problem at the upper level into a single-objective upper-level coordination problem and a multi-objective lower-level optimization problem. Li *et al.* [3] have developed sequential optimization and reliability assessment for multidisciplinary design optimization under a hybrid uncertainty of randomness and fuzziness. In order to solve MDO problems with uncertainty more effectively, the intelligent algorithms-based FRMDO–SORA method will be applied. Moreover, Zhang and Zhang [4] have proposed the multidisciplinary design optimization under uncertainties that is based on BLISS and PMA. Their future research seems to be focused on considering more one type of uncertainties. Yao and Chen [5] have extended sequential optimization and mixed uncertainty analysis (SOMUA) algorithm that was developed for single disciplinary RBO for accounting mixed aleatory and epistemic uncertainties to be applied for mixed uncertainty-based RBMDO procedure MUMDF-CSSO. One limitation to implement MUMDF-CSSO for complex system with close coupled interdisciplinary relationships is the issue of how to rationally decouple the different disciplines, which is of great importance for the efficiency of reliability analysis as well as the solving process of the whole UMDO problem. In addition, a variety of methods have been proposed to use approximation in collaborative optimization (CO). Notably, Zhang *et al*. [6] have developed a PMA-based collaborative strategy for reliability based-design and optimization of the multi- disciplinary systems. The main idea here is the decoupling of traditional triple-level nested flowchart of RBMDO through sequential optimization and reliability assessment (SORA).

Performance of wind turbines can be negatively affected by uncertainties. Due to this, more studies combining MDO with uncertainty quantification in wind turbine complex system are needed, along with a better understanding of the nature of the uncertainties associated with the environmental conditions, physical processes, and cost metrics. There are already some studies introducing MDO problems in wind turbine category but these algorithms are only concerned with deterministic objectives rather than the non-deterministic objectives. More recently, Nicholson *et al*. [7] have proposed a multi-objective structural optimization of wind turbine tower and foundation systems using Isight. Furthermore, McWilliam *et al*. [8] have extended a framework for aeroelastic multidisciplinary design optimization of horizontal axis wind turbines. Maki and *et al*. [9] have also proposed a multi-level optimization analysis to be performed on a system design of a three-bladed horizontal axis wind turbine. The top-level objective is to minimize the cost of turbine's energy production and a detailed cost-model is used. In this case, two disciplinary level optimizations are conducted simultaneously. The first designs the geometry of the blade to maximize annual energy production (AEP) while the second configures the structure of the blade. Additionally, Bottasso *et al*. [10] suggested multi-disciplinary constrained optimization of wind turbines, which was intended to obtain minimum weight in the constrained sizing of the rotor blade. Besides, there are some literatures in wind turbine category directly nested in the optimization under uncertainty that are not multidisciplinary design optimization in wind turbine. For instance, Petrone and *et al*. [11] considered variability in the wind conditions, manufacturing tolerances and roughness induced by insect contamination as sources of uncertainties and simultaneously treated all of them in a probabilistic framework using Latin hypercube sampling and stochastic simplex colocation. After that, the estimation and analysis of horizontal axis wind turbine performance under uncertainty is carried out. In addition, a lot of work has also been done on improving reliability based robust design optimization but these literatures are not concentrated on the multidisciplinary design optimization like those presented in [12]-[17].

Looking at the present state of the research in wind turbine system design as roughly indicated by the above discussions, this paper aims to present an effective RBMDO model under uncertainties for the wind turbine system based on BLISS and PMA.

II. MDO Architecture

MDO architecture refers to the combination of the design problem formulation and the organizational framework that is used to solve it. A lot of architectures have been developed such as Individual Design Feasible (IDF), Multidisciplinary Feasible (MDF), Collaborative Optimization (CO), Bilevel Integrated Systems Synthesis (BLISS) and BLISS 2000 [18]. However, here we introduce two last ones. The workflows for architectures are defined using the extended design structure matrix (XDSM) notation proposed by Lambe and Martins [19] for all the test problems. XDSM diagrams describe both data and process flows, providing a complete description of the algorithm. In short, the thin black lines in the diagram are describing the process flow by indicating the order the blocks are executed. The thick gray lines describe the movement of data, with vertical lines indicating inputs to a given block and horizontal lines indicating outputs. All parallelogram blocks are data blocks that represent variables while the other blocks represent components or drivers in the analysis. The stack of any given block type that has an *i* in the title (e.g., analysis *i*), indicates that *n* such blocks exist and may be run in parallel if desired. Each step in the process is given a numeric label (the first step in the process is always zero) that applies to both the process flow and the data flow. For process flow, labels are used to indicate loops (e.g., solver loops, optimizations). For example, in Fig. 1, the optimization loop for the individual design feasible (IDF) architecture is assigned with the label "0; 3 → 1." This indicates that starting at 0, one will follow the path from 1 to 2 to 3, and returns to step 1 and continues looping until an optimum is reached. The numeric labels in the data blocks indicate the step during which the data are either input to or output from the block.

A. Bi-Level Integrated Systems Synthesis (BLISS)

BLISS [20] operates on a series of linear approximations of the actual objective function and constraints. To derive those approximations, the architecture can use either a numerical finite difference engine or analytic derivatives. For system- level problem, sensitivities are only taken with respect to the global variables. Likewise, for the discipline-level problem, the sensitivities are only taken with respect to the local design variables that are unique to specific discipline. The general process is to generate a linearized approximation of the system, optimize with respect to that approximation, and then generate a new linearized approximation at the optimum point. Target variables are created for all the design variables, and fixed point iteration is used to converge the targets with the design variables. The defining feature is that no optimization ever occurs directly on the actual discipline analyses, only on the approximate models. BLISS uses move limits, Δxi limit, to constrain the distance the optimization can move during one iteration. For this work, the move limit was set to 5% of the initial value for any given design variable. To enforce the system compatibility, BLISS uses a solver to perform MDA for each major iteration. Hence, the coupling variables do not show up in the problem formulation. The major iteration for BLISS is controlled by a fixed point iteration that checks to see if the design variables have converged to within specified tolerance between the current and previous iterations. For this sample work, the lowest value of tolerance that can be used without always hitting the maximum iteration limit was 0.005. Since BLISS operates on linear approximation for the actual system, it can be difficult to get this architecture to converge very tightly. This tolerance should not be confused with the specific tolerance on the optimizers used in the sub-problems of BLISS, which remained at 1×10^{-6} so as to be consistent with the other cases investigated.

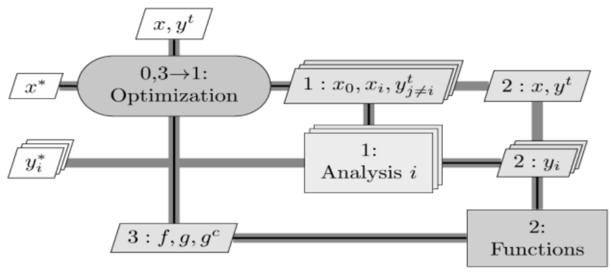

Fig. 1. XDSM diagram for sample IDF architecture [18].

The XDSM for BLISS is shown in Fig. 2. Steps 5 and 8 from Fig. 2 indicate the explicit calculation of discipline and system level sensitivities. These sensitivities are then used to construct a linearized model that is optimized.

B. Bilevel Integrated Systems Synthesis 2000

BLISS-2000 [21] is a reformulation of the original BLISS algorithm developed to eliminate the need for calculating sensitivities on the MDA. BLISS-2000 does not perform an MDA at all. It uses an IDF-like formulation to drive the system level problem, which is run on quadratic response surface approximations of the system. The XDSM for BLISS-2000 is shown in Fig. 3. Note from the XDSM that the major iteration is controlled by a convergence check that operates similar to the one used in BLISS. It checks to see how much the design variables are changing and stops when they differ by less than a given tolerance between two iterations. Again, similar to BLISS, because BLISS-2000 operates on approximations for the true system, it can be difficult to reach tight convergence levels for the design variables. Hence, just like for BLISS, the convergence tolerance of the major iteration loop is set to 0.005, though the sub problem optimizations still converge to the tighter $1\times10{-}6$. As seen in Fig. 3, in step 5 of the process, a metamodel for each of i disciplines must be created based on training data. These data are collected by executing a LatinHypercube DOE.

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C. MDO Parallel Processing

There are many schemes to classify parallel computers that have been proposed so far but none of them has become the standard. For this study, well-known Flynn's taxonomy will be used: SISD (Single Instruction Stream, Single Data Stream), SIMD (Single Instruction Stream, Multiple Data Stream), MISD (Multiple Instruction Stream, Single Data Stream) and MIMD (Multiple Instruction Stream, Multiple Data Stream) [22]. The parallelization schemes that have been proposed for the Multi Objective Evolutionary Algorithms (MOEAS) are derived from well-known models or paradigms designed for single-objective optimization such as the master-slave model, the island model, the diffusion model and the hybrid model. Once convinced of MOEA's effectiveness (how well it solves the problem), it is of a great interest to increase its efficiency (how "quickly" or "cheaply" it could solve the problem). The desire to reduce execution time and/or resource expenditures leads to consideration of parallel and distributed processing techniques [23]. Many multi-level MDO architectures can potentially allow for parallel execution of the local-level disciplines. In parallel execution, system-level optimizer will provide a set of inputs to all local-level disciplines, which they can apply to perform local-level optimization simultaneously.

This contrasts to a sequential execution where each of the disciplines must go in a specific order such that it can pass its outputs to other disciplines down the line. Parallel execution, if efficient, could result in large time savings for the entire optimization process. The savings are anticipated to be most significant for large problems where several of the disciplines involved take a lot of time and effort to execute local-level sub-problem design and optimization.

III. Proposed Strategy for Wind Turbine Design

In this study, a multi-level system design (MLS) algorithm is utilized for the wind turbine system analysis. The Cost of Energy (COE) comprises the overall system level objective while the performance improvements at two technical design disciplines are pursued at the same time. The disciplines are corresponding to the optimal design of the blade geometry for maximum annual energy production (AEP) and the structural design of the blade for minimum bending moment at the root of the blade. Main characteristics of the wind turbine, namely rotor diameter, rotational speed, maximum rated power, hub height, structural characteristics of the blade and geometric characteristics of the blade (distribution of thickness, twist angle, and chord) are employed as the design variables for the overall design analysis. In addition, the reliability of the blade is also included in this proposed framework and consideration of this aspect of the structure will likely increase the relative influence on the COE. The rest of this paper is structured as follows. Implementation of deterministic multi-disciplinary design optimization of a wind turbine is discussed in sections A, B, C and E. Furthermore, section E introduces a strategy for non-deterministic multi-disciplinary design optimization of a wind turbine. Finally, some conclusions are given.

A. Discipline 1: AEP

The first discipline level optimization is to maximize the AEP of the design. The AEP is determined using output from the wind turbine program and is based on the blade geometry from the genetic algorithm (GA) optimization output. Here, the wind is assumed to be constant over the rotor area but will vary depending on the hub height according to (1) where V is the wind speed at the hub, V_{ref} is the reference wind speed at the reference hub height and H_{ref} is the reference hub height.

$$V = V_{ref}\,(\frac{HubHt}{H_{ref}})^{0.34} \qquad (1)$$

Equation (1) takes into account the improved wind that a taller tower will provide to the rotor. Power-law coefficient of 0.34 is appropriate for neutrally stable air above the human- inhabited areas [24]. The main output from this wind turbine performance program is the power generated by the design for a range of wind speeds. The power curve is used to calculate the AEP by assuming the probability of occurrence of wind at any height follows a Rayleigh-distributed trend as dictated in (2), where V_m is the mean wind speed at the hub height. The mean speed, V is determined using (1).

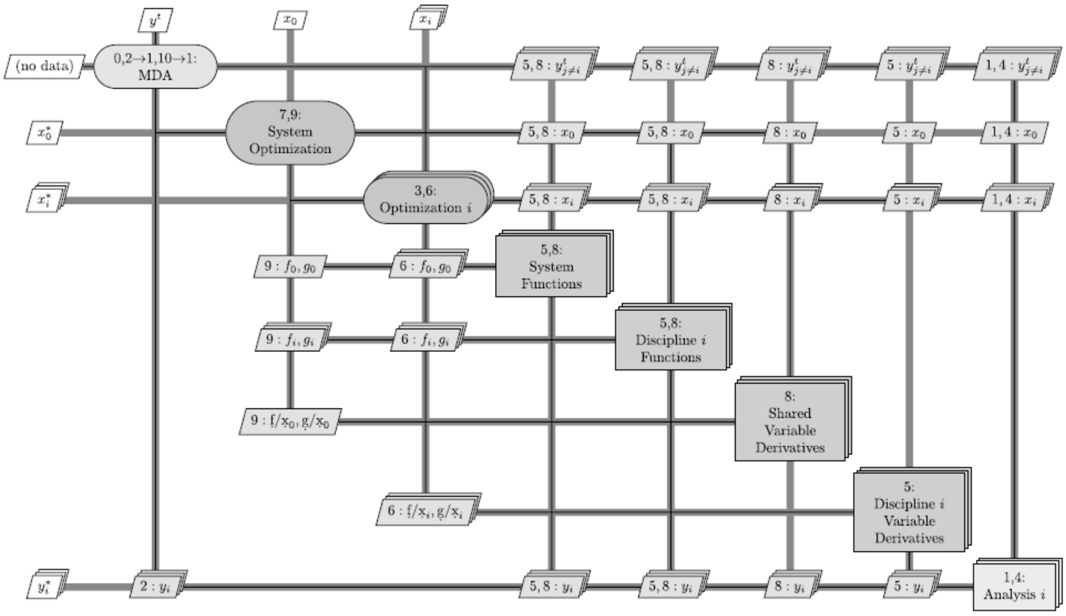

Fig. 2. XDSM diagram for sample BLISS architecture [18].

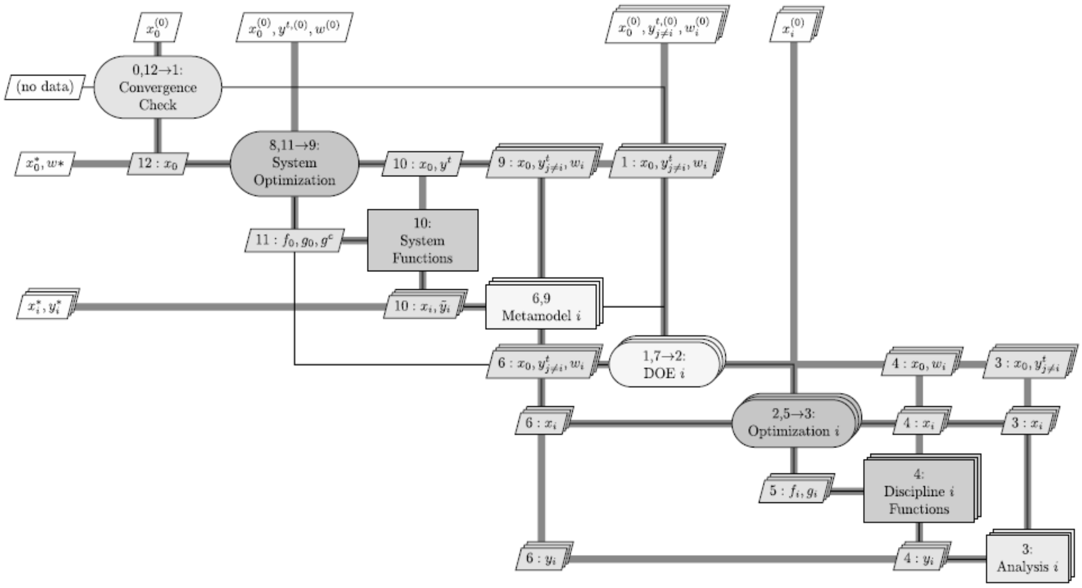

Fig. 3. XDSM diagram for sample BLISS-2000 architecture [18].

$$p(V) = \frac{\pi}{2}\frac{V}{V_m^2}\exp\left[-\frac{\pi}{4}\left(\frac{V}{V_m}\right)^2\right] \tag{2}$$

Finally, the AEP is calculated using (3). This integral can be numerically approximated with a trapezoidal rule.

$$AEP = 8760\int_0^\infty P(V)\,p(V)\,dV \tag{3}$$

B. Discipline 2: Blade-Root Bending Moment

On the other hand, the second discipline seeks to minimize blade-root bending moment. The blade loads are determined with the aero-servo-elastic time-domain simulator program that relies on inputs from several other programs. Specifically, the structural properties are found with structural properties of a composite blades program while the mode shapes of the tower and blade are determined by the modes program. The input wind time series is specified by the IEC Wind program. Moreover, the feasibility constraints are imposed on the blade sectional geometry (see Fig. 4 for a pictorial definition of the blade variables). For instance, the thickness of the shell and the web should decrease monotonically with the increasing spanwise coordinate. Also, the thickness of the shell, t_s and web, t_w must satisfy the following inequality constraints as in (4) and (5) in terms of the maximum blade sectional thickness, t, respectively. Another constraint to be imposed is to ensure that the largest strain in the blade does not exceed the limit of the given maximum in each one of the sections of the blade.

$$t_s \le \frac{1}{2}t \tag{4}$$

$$t_w \le 2t \tag{5}$$

C. Overall System Objective: Cost of Energy (COE)

To estimate the COE, the analysis will employ the model as proposed in. This report provides a cost estimation procedure that is based on existing designs to develop scaling relations to systematically estimate the COE for new turbines. Mathematically, the COE is calculated using (6) where COE here is the leveraged cost of energy ($/kWh), FCR is the fixed charge rate (1/yr), ICC is the initial capital cost ($), AEP is the annual energy production (kWh/yr) and AOE is the annual operating expenses ($/yr).

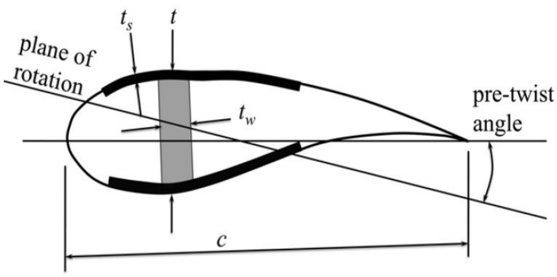

Fig. 4. Blade section diagram.

$$COE = \frac{FCR \times ICC + AOE}{AEP} \tag{6}$$

Equation (6) is the ratio of the cost to produce the energy to the amount of energy that is produced. The AEP is calculated by combining the output of relative wind turbine performance program with the assumed Rayleigh-probability distribution of the wind. The total cost of energy production is the initial capital cost multiplied with the fixed charge rate (FCR×ICC) and the annual operating expenses (AOE). The fixed charge rate accounts for the amount per dollar of initial capital cost needed to cover the various fixed charges such as construction financing and associated fees, depreciation, taxes and also insurance. The value of 0.1158/yr is suggested in the technical report of Fingersh and et al. [25], which is based on the research conducted by LWST (Low Wind Speed Technology) projects that were supported by US Department of Energy. The initial capital cost includes the cost of the turbine capital cost (TCC) and the balance of station (BOS).

$$ICC = TCC + BOS \tag{7}$$

Here, the TCC includes tower, control system, drive train, and rotor. The BOS accounts for items such as the foundation, transportation from the manufacturing site to operational site, and assembly. Also, BOS takes into account the engineering services and the cost of any required permits. In (6), the AOE includes the operation and maintenance, the land lease and the replacement costs. The operation and maintenance is related to turbine maintenance, parts and supplies for equipment and facilities maintenance, and also labor for administration and support. Typically, AOE are dominated by the replacement costs and operation and maintenance.

All parameters in Eq. (6) can be estimated based on scaling relationships found in [25]. Most of the scaling relationships are based on the principle design characteristics such as rotor diameter, machine rating and tower height. All of the design variables are implicitly represented in the calculation of the COE. The blade geometry is determined based on the GA optimization results. The blade geometry is used as input to the first discipline level activity to calculate the AEP. Also, blade and tower mass are determined from Aero-servo-elastic time-domain simulator program that is executed in the second discipline.

The main variables that affect the COE are the rotor radius, maximum RPM, rated power and hub height. These variables are used to determine the AEP through the GA optimization and wind turbine performance codes and the AEP is a main parameter for COE. For example, the TCC includes the cost of equipment that is strongly dependent on the rotor radius (e.g. rotor and nacelle equipment cost), hub height (e.g. tower cost) and the rated power (e.g. nacelle equipment cost). The BOS cost is also a function of the rotor radius, hub height and rated power. The annual operating expenses are a function of the rated power and AEP. Other design variables like the web thickness and the shell thickness affect the blade mass and hence, the blade cost and COE. However, their influence on the COE is relatively small.

All in all, design structure matrix (DSM) for the proposed Bi-Level Integrated System Synthesis of the wind turbine deterministic optimization is presented in Fig. 5.

D. RBMDO Based on BLISS and PMA

The wind turbines can generally fail due to a number of different failure mechanisms as tabulated in Table I.

TABLE I: FAILURE MECHANISMS FOR WIND TURBINES

Part/Component	Possible Failure Mechanism
Support structure	-Exceeding bearing capacity -Sliding failure
Tower	-Exceeding yielding stress -Buckling -Fatigue failure
Hub	-Exceeding yielding stress -Fatigue failure
Blades	-Global bucking -Fiber failure -Matrix failure -Inter-laminar failure -Fatigue failure

Both the sequential optimization and reliability evaluation (SORA) and the collaborative idea of BLISS and PMA are adopted in the proposed BLISS-SORA method. Therefore, the whole procedure becomes a serial sequential optimization flowchart. The multidisciplinary reliability analysis (MRA) is implemented after gaining the deterministic MDO (DMDO) results by the BLISS strategy. The MRA is implemented by the proposed a single loop MRA (SLMRA) method. As the result, high iterations of MDA and the whole computation of MRA are eliminated, and the efficiency of the whole RBMDO is improved greatly.

The whole procedures of the proposed method are shown in Fig. 6. It can be observed that the MRA is decoupled from the triple-level nested optimization flowchart. Hence the whole procedure of RBMDO is become a single level and sequential iterative optimization. The MRA is conducted after DMDO to avoid reliability analysis of all probabilistic constraints. As a result, the numbers of MDA and MRA reduced greatly.

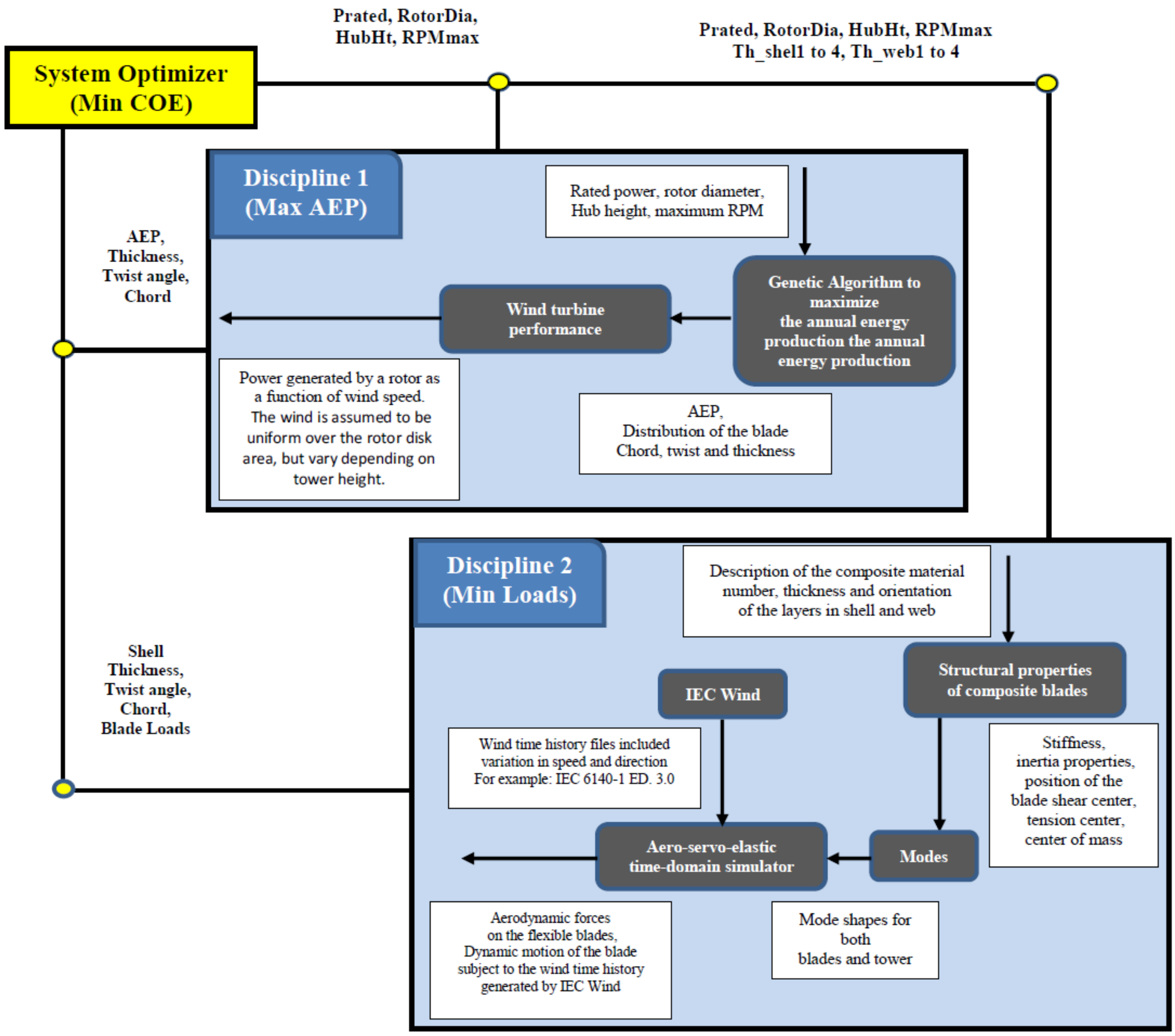

Fig. 5. XDSM for Bi-Level Integrated System Synthesis (BLISS) of the wind turbine deterministic optimization.

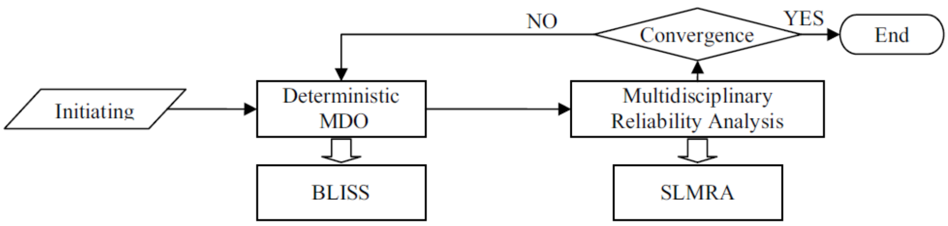

Fig. 6. Procedures of the proposed BLISS-SORA for non-deterministic multidisciplinary design optimization of a wind turbine [4].

IV. Conclusion

In this paper, we have reviewed the application of UMDO during the last few years. In addition, with the main idea of SORA, the triple-level nested RBMDO flowchart can be decoupled, and the deterministic MDO and the MRA can be executed sequentially. The whole procedure thus becomes a serial sequential optimization flowchart. The MRA will only be implemented after obtaining the deterministic MDO results by BLISS strategy. Too much iteration of multidisciplinary analysis and the whole computation of reliability analysis can be thus eliminated, and the efficiency of the whole RBMDO is improved greatly. In reliability-based optimization, it is not necessary to calculate the exact reliability for each iteration point during the optimization search and it is adequate just to judge whether the target reliability has been achieved. Hence, an alternative approach, PMA was proposed.

Also, more efforts and future researches may be focused on a mix of robust objective/reliable constraints is believed to be better suited than the original RBDO formulation for general purpose optimization, particularly when a performance target cannot be readily established for the probabilistic objective type. They involves the implementation and the testing of the proposed reliability based robust multi-disciplinary design optimization (RBRMDO) architecture, choice of uncertainty parameters and their respective probabilistic distributions, as well as the complete validation of the new analyzer modules. Special attention will be given to assessing the impact of the reliability constraints on the results, and determining whether the extra computational effort (vs. deterministic problems) is justified.

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