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A Visually-Informed Decision-Making Platform for Wind Farm Layout Optimization

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1. Abstract
Wind Farm Layout Optimization (WFLO) is a typical model-based complex system design process, where the popular use of low-medium fidelity models is one of the primary sources of uncertainties propagating into the estimated optimum cost of energy (COE). Therefore, the (currently lacking) understanding of the degree of uncertainty inherited and introduced by different models is absolutely critical (i) for making informed modeling decisions, and (ii) for being cognizant of the reliability of the obtained results. A framework called the Visually-Informed Decision-Making Platform (VIDMAP) was recently introduced to quantify and visualize the inter-model sensitivities and the model inherited/induced uncertainties in WFLO. Originally, VIDMAP quantified the uncertainties and sensitivities upstream of the energy production model. This paper advances VIDMAP to provide quantification/visualization of the uncertainties propagating through the entire optimization process, where optimization is performed to determine the micro-siting of 100 turbines with a minimum COE objective. Specifically, we determine (i) the sensitivity of the minimum COE to the top-level system model (energy production model), (ii) the uncertainty introduced by the heuristic optimization algorithm (PSO), and (iii) the net uncertainty in the minimum COE estimate. In VIDMAP, the eFAST method is used for sensitivity analysis, and the model uncertainties are quantified through a combination of Monte Carlo simulation and probabilistic modeling. Based on the estimated sensitivity and uncertainty measures, a color-coded model-block flowchart is then created using the MATLAB GUI.

2. Keywords: Model-based systems design, Particle Swarm Optimization, Sensitivity analysis, Uncertainty quantification, Wind farm layout optimization.

3. Introduction:
3.1 Model-based Systems Design
Computational approximation models are crucial building blocks of most design processes in the 21st century. This includes both physics-based models (e.g., FEA and FVM) and statistical models (e.g., surrogate models and empirical models). An informed application of such computational models demands the knowledge of how uncertainties, both inherited and introduced by such models, propagate through the model-based design process. In a broader sense, the complexity of a system and/or the inability to fully understand and address it can also be perceived as uncertainty.

There exists very few quantitative design frameworks that determine the uncertainty in the information flowing along a design optimization process, and even fewer in the arena of visualizing information attributes in the model-based design process. Allaire et al. [1] presented a new definition of system complexity and a quantitative measure of that complexity based on information theory. They performed sensitivity analysis to indicate key contributors to system complexity. This method created opportunities to use the complexity information, to make better modeling decisions, towards increasing the reliability of the resulting designs. While making a uniquely important contribution towards model-based complex system design, in its current form (that does not involve visualization), this method does not provide a strategy to actually integrate *design automation* and *human decision-making*.

In a recent paper, Chowdhury et al. [2] explored the hypothesis that, "such integration could be accomplished by a visualization platform that will enable the user/designer to be cognizant of the *criticality*, *fidelity*, and *expense* of information at any stage or model-level of the design process". In other words, such a visual platform will allow the designer to make informed modeling decisions in a model-based complex system design (MB-CSD) process. In that paper, a new framework concept was proposed to quantify and visualize the inter-model sensitivities (*information criticality*) and the uncertainty (*information fidelity*) introduced by each model in the process of designing wind farm layouts – this framework was called a Visually-Informed Decision-Making Platform or VIDMAP. Wind farm layout design is a complex process, which involves multiple layers of highly non-linear models and highly uncertain input parameters. In this initial implementation of VIDMAP, Chowdhury et al. [2] demonstrated a quantification and visualization of the inter-model sensitivities and model-induced uncertainties leading up to the estimation of the energy production of a 100 turbine wind farm. The VIDMAP visualization obtained thereof provided a unique illustration of which models and input parameters (in this case, turbine power response and wake width estimation models, and turbine features) have the strongest impact on the energy production estimations.

3.2 Impact of VIDMAP

The end goal of understanding (and analyzing) the inter-model sensitivities and the model-induced uncertainties along a MB-CSD process is to *accomplish a desirable level of reliability in the final solutions (or designs) at an acceptable expense and within a reasonable time-frame*. To this end, the user is required to make modeling decisions, such as: (i) *model selection*, (ii) *specification of prescribed model parameters and/or kernel functions*, (iii) *sampling or design of experiments*, (iv) *model improvement*, (v) *grid refinement*, and (vi) *computational resource allocation*. These modeling decisions can be partly automated and partly user-guided (through informed decision-making), only if measure(s) of pertinent information attributes are available to guide quantitative decision-making. With VDIMAP, we are exploring the potential of constructing and using a novel platform that quantifies and provides a visual representation of these information attributes.

In this paper, we are presenting a significant advancement to the development and implementation of VIDMAP, with the following research objectives:

1. Develop a computationally-efficient approach to exploit the previously quantified uncertainty in the top-level system evaluation model in estimating the sensitivities and uncertainty of the final optimum design, where the system evaluation model itself comprises several uncertain downstream models.
2. Quantify the uncertainty introduced by a heuristic optimization algorithm into the final optimum design.
3. Apply the new VIDMAP to the entire wind farm layout optimization (WFLO) process, thereby extending the visualization platform from the ”energy production model” (demonstrated in [2]) to the optimum Cost of Energy (COE) obtained by WFLO.

A brief discussion of the wind farm layout optimization (WFLO) process and existing methods in this arena is provided in Section 4.1. Sections 4.2 and 4.3 respectively provide an overview of VIDMAP and the advancement of VIDMAP (undertaken in this paper) in order to apply it to the entire WFLO process. Illustration and discussion of the results obtained from the application of the advanced VIDMAP to WFLO is provided in Section 5.

4. An Informed Approach to Model-based Design of Wind Farm Layouts

4.1 Wind Farm Layout Optimization

The energy losses in a wind farm due to wake effects can be reduced by optimizing the selection and the arrangement of turbines over the site, a process commonly known as *wind farm layout optimization* (WFLO). Two primary classes of turbine arrangement (or layout optimization) methods exist in the literature: (i) methods that divide the wind farm into a discrete grid in order to search for the optimum grid locations of turbines [3, 4, 5, 6], (ii) more recent methods that define the turbine location coordinates as continuous variables, thereby allowing turbines to take up any feasible location within the farm [7, 8, 9]. A few of the above methods also allow optimal selection of commercial turbines along with optimal turbine arrangement [9, 10]. A majority of these *wind farm layout optimization* methods seek to either maximize energy production or minimize the cost of energy (COE).

In this paper, we use the Unrestricted Wind Farm Layout Optimization framework [9], as it is one of the most comprehensive WFLO frameworks in terms of the variety of design and natural factors that it incorporates in the process of searching for the most optimal wind farm layouts. More specifically, the energy production model [9], the land usage model [11], and the optimization methodology [9] used in demonstrating VIDMAP are all adopted from the UWFLO framework. In UWFLO, the COE (in \$/kWh) of a wind farm is expressed as

$$COE = C_{farm}/E_{farm} \tag{1}$$

where C_{farm} and the E_{farm} are respectively the average annual cost (in \$) of the wind farm and the average annual energy production (in kWh) of the wind farm. There are several wind farm cost models in the literature [12, 13, 14], which are generally empirical in nature, and represent cost in terms of different sets of parameters such as turbine features, nameplate capacity, and labor costs. The *energy production model* in the UWFLO framework is a complex model that represents the wind farm energy production as a function of the turbine features, turbine locations, and the incoming wind conditions over a given period of time.

The energy production model is a collection of several models: (i) the *wind distribution model* that estimates the frequency of wind speeds based on the measured site data; (ii) the *wind shear model* that determines the wind speed at a given height above the ground (generally the hub height) based on measured/reference wind speed at a different height; (iii) the *wake model* that estimates the wake width and the wind speed in the wake downstream from each turbine within the farm; and (iv) the *turbine power response model* that yields the power generated by each turbine with respect to the wind speed directly encountered by the turbine. The energy production of the wind farm (E_{farm}) is estimated as a numerical integration of the wind farm power generation over a distribution of wind conditions, which can be expressed as:

$$E_{farm} = (365 \times 24) \sum_{i=1}^{N_p} P_{farm}\left(U^i, \theta^i\right) p\left(U^i, \theta^i\right) \Delta U \Delta\theta, \quad \text{where } \Delta U \Delta\theta = U_{max} \times 360^\circ / N_p \tag{2}$$

where $P_{farm}\left(U^i, \theta^i\right)$ represents the power generated by the farm (in kW) for the i^{th} sample wind speed (U^i) and direction θ^i $-$ estimated using the wind shear model, the turbine power response model, and the wake model. In Eq. 2, $p\left(U^i, \theta^i\right)$ represents the probability of the occurrence of the i^{th} sample wind wind condition, which is given by the wind distribution model. The parameters U_{max} and N_p are respectively the reference maximum wind speed at a site (e.g., 15 m/s) and the number of sample wind conditions considered (20 in this paper).

Wind farm layout optimization (WFLO) can be readily perceived as a complex system design process. The energy production of a wind farm depends on several compound factors, such as (i) atmospheric boundary layer (ABL) variations, (ii) local topography, (iii) turbine geometry, (iv) turbine power characteristics, (v) arrangement of turbines over the site. These factors themselves comprise of multiple sub-factors or characteristics; e.g., the ABL, even in its simplest representation, consists of (i) mean wind speed and direction, (ii) turbulence intensity, (iii) wind shear, and (iv) air density, all of which vary with time and space. Several of these factors are highly uncertain, and the implicit functional relationships are highly nonlinear. In addition, high-fidelity estimations of some of these functional relationships have extensive computational footprint, making them practically prohibitive in the context of designing utility-scale wind farms $-$ e.g., with current high-fidelity LES wake models (e.g., NREL SOFWA), one will require approximately 600 million CPU-hours for optimizing a 25-turbine wind farm [15, 9].

WFLO thus comprises a series of interdependent/interconnected models. A information flow perspective to WFLO can therefore enable significant advancements in informed decision-making compared to the state of the art. VIDMAP provides such an information flow visualization for WFLO through a synergistic implementation of *sensitivity analysis*, *uncertainty quantification*, and a novel *visual interface*. In its complete form, *VIDMAP could provide a major leap forward not only in addressing issues of "wind farm underperformance" and "concept-to-installation delays", but also in effective "risk mitigation" in wind energy projects*. The following section describes the major components of VIDMAP in the context of WFLO.

4.2 Visually-Informed Decision-Making Platform (VIDMAP)

The Visually-Informed Decision-Making Platform (VIDMAP) for WFLO comprises the following 3 components:

1. *Uncertainty Quantification*: Uncertainty quantification (UQ) is in general performed in VIDMAP to gauge the fidelity or quality of information at any stage in the design process; in other words, UQ techniques are applied to estimate the uncertainty in the *originating information* (i.e., inputs to the most upstream models), and to subsequently estimate the uncertainty generated by the models (themselves) along the design process.

2. *Sensitivity Analysis*: Sensitivity analysis is performed for each constitutive model (in the design process) to gauge the relative impact of different inputs (incoming information) on the model output (outgoing information). It essentially illustrates the inter-model dependency/sensitivities within the design process.

3. *Informed Graphical Representation*: A graphical user interface (GUI) is created to illustrate the *uncertainty in the information generated by each model* and the *inter-model sensitivities*.

The VIDMAP GUI is therefore intended to be an important step towards integrating *design automation*, *evolving heuristics*, and *human decision-making* in the context of model-based design. The VIDMAP GUI is developed using the MATLAB GUI toolbox, and associated built-in functions. The initial VIDMAP GUI constructed in [2], which shows the entire WFLO framework and specifically illustrates the estimated inter-model sensitivities and model uncertainties up to the energy production model stage, is shown in Fig. 1.

In Fig. 1, the color bar shows a qualitative representation (e.g, high/low) of the uncertainty and sensitivity. Variance is used as the measure of uncertainty, and is normalized w.r.t. reference values to allow ready comparison across different models. The measure of sensitivity used in this case is the variance-based first-order index, which can take any positive real value less than or equal to 1. These sensitivity indices are estimated using the Extended Fourier Amplitude Sensitivity Test (eFAST), developed by Saltelli and Bolado [16].

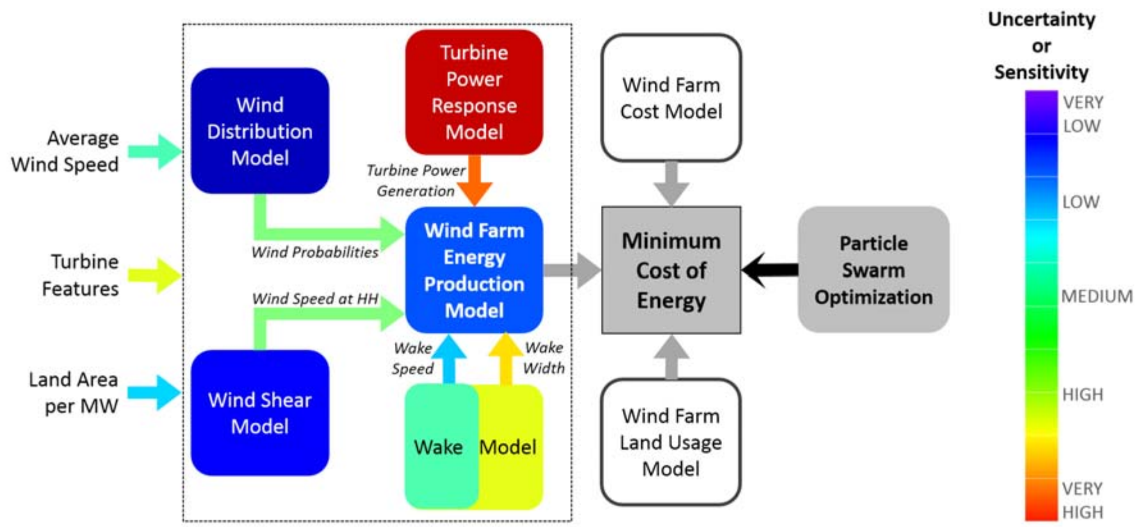

Figure 1: The VIDMAP graphical interface for WFLO, where (i) the color of a model block depicts the uncertainty in the corresponding model output;(ii) the color of a connector depicts the sensitivity of the corresponding downstream model output to the upstream information-source; and (iii) a gray-colored block or connector indicates that the corresponding sensibility or uncertainty values have not yet been computed

The approaches used to quantify the uncertainty in the upstream models, and propagate the uncertainty downstream, is further described in [2] In this paper, we particularly extend the VIDMAP for WFLO to estimate the uncertainty introduced by the PSO algorithm, the sensitivity of the minimum COE (associated with the optimized layout) to the uncertainties in the "energy production model", and the resulting uncertainty in the minimum COE. The WFLO problem definition and the VIDMAP advancements are discussed in the next Section.

4.3 Advancing VIDMAP for WFLO

The objective of wind farm layout optimization here is to minimize the cost of energy (COE) of a 100-turbine wind farm, for given (i) turbine type(s), (ii) maximum allowed land area per MW installed (LAMI), (iii) land aspect ratio, and (iv) wind distribution. A Rayleigh distribution of wind speed is considered, where the single-parameter Rayleigh distribution is estimated from the given *average incoming wind speed* (U_{av}). The variables in the optimization problem are the locations of each turbine (X_j,Y_j) − a total of 200 design variables. The optimization problem is defined as

$$
\begin{aligned}
&\underset{V}{\text{Min}} \quad f = COE\,(V,T) \\
&\text{subject to} \\
&\qquad g_1\,(V) \le 0 \\
&\qquad g_2\,(V) \le 0 \\
&\qquad V = \{X_1, X_2, \ldots\ldots, X_{100}, Y_1, Y_2, \ldots\ldots, Y_{100}\}
\end{aligned}
\tag{3}
$$

where the COE is estimated from Eq. 1; T represents the turbine type (a vector of features for a given commercial turbine); the inequality constraint g_1 represents the minimum clearance required between any two turbines, which is set at "2 × rotor diameter" of the installed turbines; and the inequality constraint g_2 represents the maximum allowed LAMI (A_{MW}). Since a land aspect rario of 7/3 is assumed, the farm dimensions can be estimated from the maximum allowed LAMI as: $L = \sqrt{7/3 \times 100 A_{MW}}$ and $B = \sqrt{3/7 \times 100 A_{MW}}$.

In order to decouple the variance of the *energy production model* from that of the independent parameters, the deviation in the output (E_{farm}, given by Eq. 2) of the energy production model is represented by a stochastic parameter (ε_E) that follows the probability distribution determined via uncertainty propagation in [2] − where E_{farm} had an estimated variance of 0.0063. Thus, the return value from the energy production model (the top-level system evaluation model) whenever it is called by the optimization algorithm is given by $f_E = E_{farm}\,(1+\varepsilon_E)$. The effective set of input parameters for the sensitivity analysis and uncertainty quantification of the minimized COE is provided in Table 1; this table also shows the upper and lower bounds of the input parameters, and the sampling strategy for these parameters. The first three inputs are the independent inputs, and the last input represents the stochastic deviation in the energy production estimates.

Table 1: Continuous Design variables

Input Parameter	Lower Bound	Upper Bound	Sampling Strategy
Average Wind Speed (U_{av})	3.5 m/s	10.0 m/s	Normal Distribution with mean= 5.6m/s and $\sigma = 1.3$m/s [17]
Turbine Feature Vector (T_i)	$i = 1$	$i = 24$	Uniform
Land Area per MW (A_{MW})	10 ha/MW	50 ha/MW	Uniform Pseudorandom (LHS) [2]
Deviation in WF Energy Production (ε_E)	-∞	∞	Normal Distribution with zero mean and $\sigma = 0.079$ [2]

Based on the information provided in Table 1, a mixture of 50 samples is created with the following three parameters: Average Wind Speed (U_{av}), Land Area per MW (A_{MW}), and Deviation in WF Energy Production (ε_E). WFLO is then performed for each sample w.r.t. each turbine type (turbine feature vector). For the sake of computational efficiency, a small set of 24 different turbine types are chosen from the comprehensive list of 131 commercial turbines considered in [2]. Therefore, WFLO is performed for a total set of $50 \times 24 = 1200$ samples.

Heuristic optimization algorithms such as particle swarm optimization (PSO) and genetic algorithms (GA) involve random operators, and are also initiated with randomly generated population of candidate designs. As a result, the optimum solution obtained by such heuristic optimization algorithms could vary from one run to another. Hence, these algorithms are generally run multiple times to gauge their robustness during benchmark testing or practical application. In this paper, WFLO is performed using the mixed-discrete PSO adopted from the UWFLO framework [18]. The uncertainty introduced by the PSO algorithm (due to its random operators) is estimated by running WFLO with this algorithm 5 times for each of the 1200 samples. The number of optimization runs per sample although small is considered practically adequate, since the observed variance in the PSO results was small, and it also helped in retaining desirable computational efficiency of the overall VIDMAP framework. The uncertainty in the estimated minimum (σ_f^{PSO}) due to the PSO algorithm is then determined by

$$\sigma_f^{PSO} = \frac{stddev\left(f_1^{PSO}, \ldots, f_5^{PSO}\right)}{min\left(f_1^{PSO}, \ldots, f_5^{PSO}\right)} \tag{4}$$

where the generic f_k^{PSO} represents the optimum value of the objective function obtained in the k^{th} run of PSO for a given sample. The resulting VIDMAP GUI for the overall WFLO framework is illustrated next.

5. VIDMAP for WFLO: Results

It is observed from Fig. 2 that the optimization algorithm is significantly robust with an average estimated variation in the obtained minimum over 5 runs (for each sample) of only 0.12%. This observation further establishes the use the PSO as a suitable algorithm for WFLO. The sensitivity of the computed minimum COE to the energy production model appears to be small (from Fig. 2) due to the first order index of 0.00118. However, it is to be

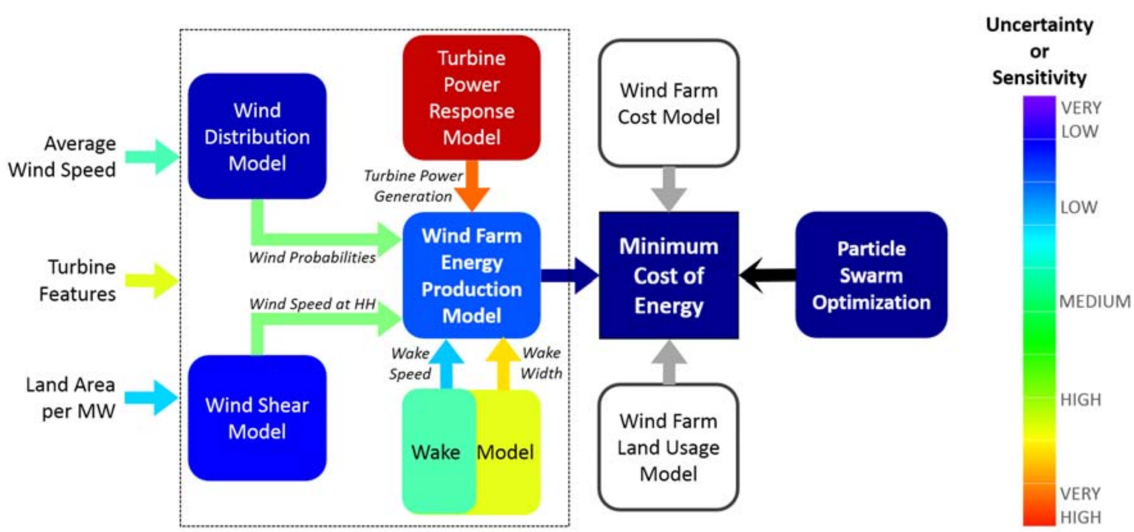

Figure 2: The final VIDMAP graphical interface for WFLO; gray colored blocks represent deterministic models; otherwise the color of a block represents the corresponding model uncertainty

noted that the total order index of the deviation in the output of the energy production model is estimated to be 0.87. This observation indicates that the impact of the uncertainties in the energy production model is highly coupled with the variation in the wind resource, allowed land usage, and selected turbine features. Hence, the uncertainty in the energy production model is likely to influence decision-making when multiple wind farm sites, multiple turbine configuration, and different land plot availability is being considered in the planning stage of wind farm development. Moreover, it indicates that VIDMAP needs to be further advanced to illustrate both the first and total order indices with respect to inter-model sensitivities.

6. Concluding Remarks

In this paper, we advanced the Visually-Informed Decision-Making Platform to understand and analyze the impact of the uncertainties in the system model and the heuristic optimization algorithm on the uncertainties in the minimum Cost of Energy (COE) obtained through wind farm layout optimization. VIDMAP was applied in the layout optimization of a 100 turbine wind farm, where 1200 different samples of allowed land usage, wind resource strengths, turbine configurations, and (previously quantified) deviations in the energy production estimates are used to perform the sensitivity and uncertainty analysis. The uncertainty due to the random operators in the optimization algorithm (Particle Swarm Optimization) was determined by running the algorithm 5 times for each sample. It was observed that the Particle Swarm Optimization algorithm is remarkably robust, whereas the total order sensitivity of the minimum COE with respect to the deviations in the energy production estimates and the input parameters was noticeable.

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