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Commentary

Monitoring Complexity in Clean Energy Systems Applications

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ABSTRACT: Clean energy applications often involve systems with technological process monitoring. This supervision aims to optimize operation, in particular efficiency, performance and compatibility with dedicated criteria. Most of these energy systems involve complex procedures. A complex procedure is an arrangement of compound processes interacting in interdependent behaviors. The supervision of these complex procedures focuses on the interaction of compound processes, their digital coupling and the handling of uncertainties in their detection and digital tools. Real-virtual pairs, such as digital twins, could carry out such surveillance. This commentary aims to analyze and illustrate such supervision in clean electromagnetic energy systems based on a review of the literature. The notion of complexity and the interactions of the compound processes involved are first addressed and detailed. The modeling of these interactions is presented through the mathematical coupling of the electromagnetic equations with other equations of the phenomena involved. These phenomena are linked to the functional or environmental behaviors of the systems. Compound process monitoring in complex procedures is then analyzed taking into account threats, unsolicited external events and uncertainties related to the sensing and digital tools involved. This contribution illustrated several points relating to, the relationship between the complexities of a real energy procedure and its coupled virtual model, the dependence of the model reduction strategy on each specific application and the reduction of uncertainties through the matching of real-virtual pairs. The different analyses are supported by literature references permitting more information when necessary.

Keywords: Complex procedures; Interaction; Electromagnetic; Interdependent behaviors; Mathematical coupling; Supervision; Uncertainties; Real-virtual pairs

1. Introduction

In today's clean energy activities, complex procedures play a central role. Additionally, increased computing capabilities have enabled machines to perform tasks ranging, from simple automated operations, up to more sophisticated operations as, autonomous energy systems. Very often, clean energy uses electrical and electromagnetic means. Complex electromagnetic procedures use skillful control tools to monitor their behavior, which is strongly linked to the accuracy of their integrated control model.

Complexity can be encountered in addition to industrial systems, e.g., [1–7], in various fields, e.g., neuroscience [8] Earth climate [9], space vehicles [10], computer vision [11], economics of fair division [12], game theory of strategic interactions [13], political science [14] and history [15,16].

In general, a complex procedure is composed of a number of compound processes that interact in nonlinear interdependent spatiotemporal behaviors. Such an interaction is more complex for higher nonlinearities and closer temporal behaviors. The corresponding mathematical representation involves the coupling of process equations. Such coupling would be strong for a highly complex interaction, leading to a simultaneous solution of equations. Lower complex interactions reflect less severe and temporally distant nonlinear behavior. In this case, the coupling of the equations would be weak, characterized by an iterative solution. For linear and far temporal behaviors, the solution of the equations would be independent and the corresponding interaction is simple (not complex). The preceding discussion shows that the more complex the behaviors, the more complex the necessary models will be. In addition to taking into account functional phenomena related to compound processes, we must take into account, in the coupling

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of equations, other phenomena related to environmental conditions and undesirable side effects [17]. Additionally, unintended, accidental or unforeseen events may occur in complex procedures and we must remedy their effects.

The supervision of multifunctional clean electromagnetic energy applications involving complex procedures similar to those mentioned above, must take into account the stated functional, environmental, undesirable and accidental phenomena. When monitoring simple systems, the models built into the control are often simplified to enable rapid matching between the model and the system. Thus, such a strategy would be ruled out in the presence of complexity. One of the possible solutions to deal with this complexity would be to use the real-virtual pair strategy. Such a technique can perform adaptive dynamic operation in real time, which would cut off or reduce sensing and digital uncertainties as well as accidental events. The digital twin concept employ such real-virtual pair [18–20].

The aim of this commentary is to analyze and discuss the mathematical coupling of interactions in complex procedures and their supervision in clean electromagnetic energy systems based on a review of the literature. The novelty of this contribution lies in highlighting the assistance of mathematical coupling and model reduction in supervising the complexity in clean electromagnetic energy procedures. In the second section, the complexity and the interactions of the compound processes involved are addressed. The third section, focus on the modeling of such interactions through the mathematical coupling of the equations related to electromagnetic and other phenomena implicated in the functional and other behaviors of the systems. Compound process monitoring in complex procedures is then analyzed in section 4, taking into account threats, unsolicited external events and uncertainties related to the sensing and digital tools involved. Section 5 is focused on the discussion of additional related matters and concluded remarks of this commentary. In all sections, analyses and illustrations are supported by literature references for more information if necessary, and not for literature assessment.

2. Complexity and the Interactions of the Compound Processes

As mentioned previously, the degree of complexity is linked to the degree of non-linearity of interdependence of the interactions as well as to the degree of proximity of temporal evolution; these perform complexity spatiotemporal behavior. The degree of complexity can be classified in terms of interactions [21]. These can be categorized corresponding to their growing complexity into three interactions natures: simple, complicated and complex. The first performs directly; complicated one behaves loosely coupled while complex interaction behaves tightly coupled. The difference between the last two is that complicated interaction does not change its conduct while the complex one is adaptive. Thus, for a given initial state, one can predict the outcome of complicated case whereas in complex one, the outcome will be subject to the interacting processes. Such complex adaptive interactions can be found in different circumstances of natural and artificial events; e.g., [22–25].

Modeling the interactions of processes involved in complex procedures implicates functional phenomena as well as other undesirable phenomena and side effects. The mathematical equations governing the behavior of these phenomena are generally solved in the harmonic or temporal domains in three-dimensional (3D) spatial geometry. Numerical analysis tools, such as finite element, are regularly used to perform studies of complex procedures and configurations where obtaining an analytical solution might not be possible. In addition, the solution is carried out locally to take into account the spatial non-linearity and the non-homogeneity of the material. This could be achieved with such discretized techniques allowing complex geometries to be considered. Space is divided into volume elements where variables are defined on nodes, edges, surfaces or volumes. Such mathematical modelling applied in the case of clean electromagnetic energy applications is the subject of the next section.

3. Modeling of Interactions in Clean Electromagnetic Case

This section is dedicated to the mathematical modeling of the interactions involved in electromagnetic applications of clean energies. This includes the different functional and associated phenomena and their behavioral coupling as well as intrinsic couplings of possible involved smart materials.

Note that for commodity and according to the nature of this contribution (short commentary), sets of equations will not be inserted in the text. These are replaced by open access references containing all of these equations.

3.1. Functional Phenomena Equations

Functional phenomena in energy activities are linked to the type of application. In the case of clean electromagnetic energy, these can be electromagnetic, electric (circuit), mechanical or thermal behavioral phenomena, in addition to the use of smart materials involving intrinsic combinations of these phenomena. The time constants in the first three phenomena are close and of a small value (rapid temporal evolution), while the thermal one is of a high value (slow temporal evolution). In this commentary, the equations governing these phenomena will not be detailed for commodity and they could be found in reference [17].

3.1.1. Electromagnetic Equations

The equations governing the principal involved phenomenon are those of electromagnetic fields (EMFs) [17]:

$$\begin{gathered}\boldsymbol{\nabla} \times \mathbf{H} = \mathbf{J} \\ \mathbf{J} = \mathbf{J_e} + \sigma\,\mathbf{E} + j\,\omega\,\mathbf{D} \\ \mathbf{E} = -\boldsymbol{\nabla}\,V - j\,\omega\,\mathbf{A} \\ \mathbf{B} = \boldsymbol{\nabla} \times \mathbf{A}\end{gathered} \tag{1}$$

They are in terms of the electric and magnetic vector fields **E**, **H** and inductions **D**, **B** and the current density **J**. The corresponding parameters, in addition to the radial frequency ω, are the magnetic permeability **B/H**= μ, the electric permittivity **D/E** = ε and the electric conductivity **J/E** = σ. The symbol **∇** is a vector of partial derivative operators and j imaginary symbol.

These equations set permit the computation, in addition to the different induced fields due to a given source, of the global quantities of the dissipated electric power loss P (see equation 4), the magnetic force F_{mag} (see equation 3), the magnetic flux, etc.

3.1.2. Circuit Equation

The relation of its source voltage V and its coil current i, characterize an electric circuit [17]:

$$V = 1/C.\int i\,dt + r\,i + L.\,di/dt + d\Psi/dt + \mho \tag{2}$$

This equation is in terms of, in addition to V and i, the total resistance of the circuit r, a linear inductance L, a capacitance C, a non-linear voltage drop ℧ (typically a semiconductor component, e.g., a diode) in the electrical circuit. The magnetic flux of the magnetic circuit is associated to a flux linkage Ψ in the coil, which induce an electromotive force (emf) in the electric circuit corresponding to its time derivative.

3.1.3. Mechanical Equations

Movement, displacement, vibration or deformation could characterize mechanical phenomena. A general form of an equation of a displacement due to external and magnetic forces can be [17]:

$$m.\,d^2X/dt^2 + q.\,dX/dt + k\,X = F_{mag} + F_{ext} \tag{3}$$

This equation involves the mechanical displacement X (and its first and second time derivatives: d/dt, d^2/dt^2), the magnetic and external forces F_{mag} and F_{ext}, the mass of the moving object m, the damping coefficient q, and k the spring stiffness.

3.1.4. Heat Transfer Equations

The heat transfer equation features the temperature rise due to a heat source:

$$c\,\rho\,\partial T/\partial t = \boldsymbol{\nabla}\cdot(k\,\nabla T) + P \tag{4}$$

This equation is in terms of the temperature rise T (and its time and space derivatives), heat source P, the thermal conductivity k, the specific heat c, and the density ρ of the substance.

3.2. Other Phenomena

In addition to functional phenomena, other events could be associated as environmental, side effects or accidental perturbations. These could be vibration, heating or exposures in general. The governing equations could be related to acoustics, fluid mechanics, biological, etc.

3.3. Coupled Phenomena Equations

The different functional (and possible other) phenomena equations could be solved in a coupled manner. The coupling may be weak (iterative) or strong (simultaneous). The concerned couplings involve behavioral and intrinsic in smart materials.

3.3.1. Behavioral Coupling

These are the couplings due to the interaction of different functional phenomena activated in the electromagnetic procedure. The EMF-circuit coupling is achieved via I, emf in (2) and J, B in (1). The EMF-mechanical coupling is activated by the magnetic force F_{mag} from (1) to (3). EMF-heat transfer will take place via the electrical power dissipated P from (1) to (4). Note that each of the coupled equations could affect the different parameters of the others.

3.3.2. Smart Material Coupling

The possible included smart materials in the electromagnetic procedure have intrinsic couplings. These are mainly: magnetostrictive (magnetic–mechanic), electrostrictive (electric–mechanic), shape-memory (thermic–mechanic), and thermoelectric (thermic–electric). The first concerns nonlinear behavior and close time constants and the coupling will be strong. The second behaves linear and the solution will be direct. The last two reflect distant time constants and the coupling will be weak.

4. Supervised of Complex Procedures

The monitoring of simple controlled systems use simplified models permitting fast online computations and so, a swift matching system-model. The higher precis is the model, such matching would be better but the model computing time will be higher and the speed of online matching would be lower. Thus, we need a compromise between model precision and online matching speed. Different control applications can be encountered in clean energy applications considering adaptive dynamics behaviors, predictive Control strategies and risk-constrained operations; see e.g., [26–30].

4.1. Behaviors of Complexity

In the case of complex procedures, the last discussed challenge will be more significant, because the higher the procedure complexity is, higher the model complexity will be and the longer the model computation time will be. In such complexity circumstances we need, a closer model to the real complex procedure, a lower model computing time and reduced uncertainties for both sensing and digital tasks. These borders could be approached by techniques as IoT (internet of things) or CAE (computer-assisted engineering), the first is physically supported and the second is numerically maintained. These techniques perform well in identified procedures with well-known behaviors. However, it is crucial to diminish and command the irregular and unwanted behaviors that arise in these complex procedures that comprise systematically complex interactions. Attaining such an objective necessitates a paired real—model twin experienced in the relevant procedure [19]. Such a pair diverges from both IoT and CAE by centering on both the real physical and virtual digital domains.

4.2. Real-Virtual Matching Pair

Such a pair of real-virtual allows for self-correcting behavior. The real side provides the sensing processed data to the virtual part while this latest advances control directives to the real side. Such a pairing also makes it possible to mitigate uncertainties and to alleviate all unwanted and endangering operating singularities. This matching is accompanied by processing actions. Processed information of the real side provides sensed data evaluated and reflected with external data (IoT) and the learned history. The corresponding output would be, after training, transmitted as data analytics. This processed data including indications on the reduced time appropriate model will be forwarded to the virtual simulation tool. Indeed, fast pairing requires a reliable virtual replica with low calculation time. This can be achieved by reducing the digital model while keeping the physical representation faithful. Supervision using such a pair allows adaptive control for a complex and dynamic procedure.

4.3. Digital Twin

Initially, the notion of digital twin (DT) was introduced by Grieves in 2002 [19]. A beneficial two-way tool, between the mirrored virtual and physical real spheres, typifies DT. It is constituted of three elements, which are a paired real, a real-time digital virtual element, and a processing matching link. The real part amends its conduct in coherence with the advices conveyed by the virtual part, while the latter precisely replicates the actual condition of the first. Therefore, the DT suggests a well-designed association between the real and virtual parts [20]. Certainly, it is a live two-way allied matching process, the real corrects the virtual error and the later improves the information of the first. Such succession of recurrences escorts to an added intelligent cooperation. As stated above, the concept of DT was first presented by M. Grieves in 2002, but analogous notions existed previously, as for example the NASA Apollo missions in 1970. After the disaster of the explosion of the oxygen reservoir of Apollo 13, the mission transformed high-consistency emulators to adjust them to the actual circumstances of the destroyed spaceship and used them to land securely. This was perhaps one of the highest factual uses of a DT, which had the principal features of Grieves one even though it was not a familiar concept in 1970.

4.4. Model Reduction

As discussed earlier, comprehensive procedure models are indispensable to endorse the features, running and physical reliability of complexity concerned in clean energy procedures. The growth in procedure complexity fashions the virtual models further sophisticated and therefore enlarges the calculation time. Model reduction strategies [31–33] use, can advance an attenuation in such time, whilst keeping appropriate physical precision. The spirit of such strategies is to retain only, the physical exhibitions and magnitudes of importance (for a given application), in a model of elevated intricacy, allowing a humble one that can be performed more easily. A second category reducing computation time and adapted for complex models involving discretized technique as finite elements is surrogate models (or metamodels) [34–36]. These approximately emulate the complex high-faithfulness models, using less consuming time statistical models. The choice of model reducing computation time in all strategy depends strongly on the specific requests and application objectives.

4.5. Clean Energy Applications

Complexity can be encountered in various clean energy applications such as space vehicles, airplanes, electric boats, autonomous ground vehicles, etc. These applications feature advances in mathematical modeling, dynamic exploration, intelligent supervision and diagnostics. This includes various features such as state observation, battery management organizations, autonomous steering control, driver assistance utensils, electronics, electric drive sets, connections to the electrical network, security, and health defense. Such features expose a multi-component system involving intelligent automated actions that require precise and compacted models. For example, an intelligent vehicle has augmented and cognitive perception. These are covered by a system containing radar sensors, laser scanners, cameras and actuators that enable the robotics to carry out driving tasks such as condition monitoring and autonomous navigation control. DT [37–44] can often handle supervision in such an application.

Figure 1 summarizes a real-virtual pair supervision of a complex real clean energy procedure paired to its virtual replica via a matching and processing link. This represents the different analyses and discussions involved in section 4 accounting for Sections 2 and 3.

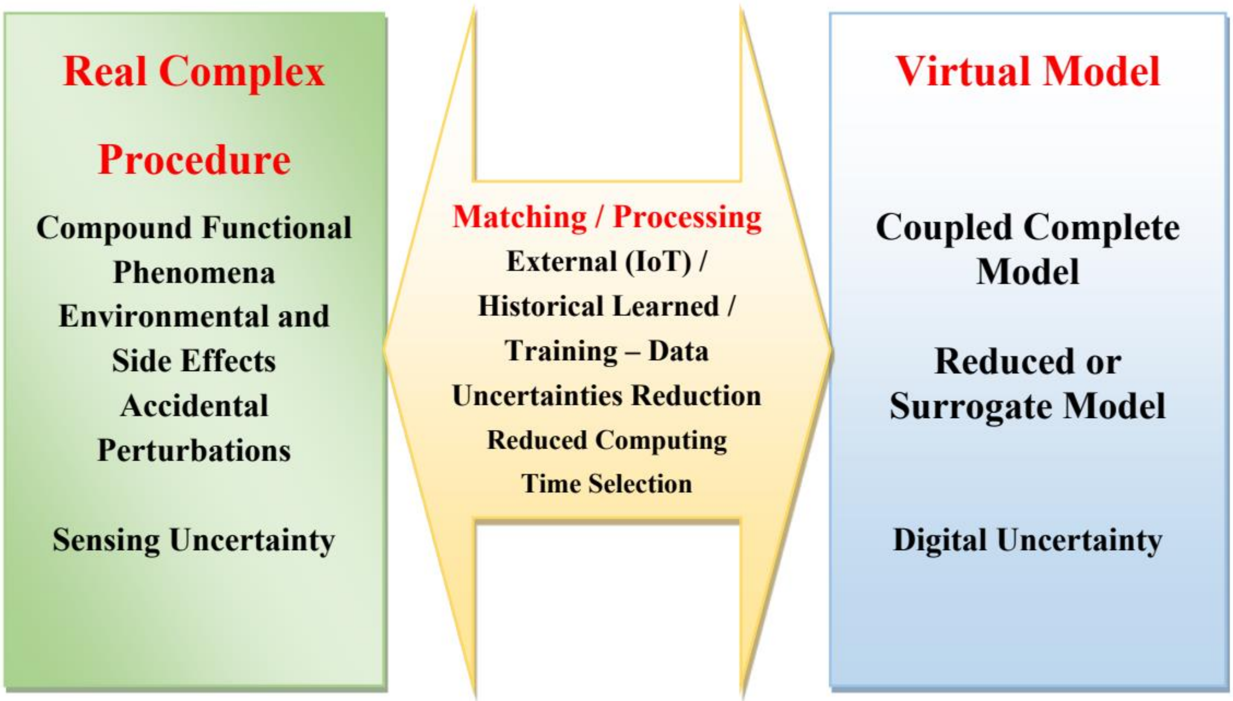

Figure 1. Summarized illustration of a matched monitoring of a complex energy procedure with its virtual model.

5. Discussion

In the present document, the investigation of monitoring the complexity of clean energy systems applications, have pointed out the benefice of such a topic. At this stage, various questions deserve to be commented:

- It should be noted that as electromagnetic energy is considered a clean source, it is subject to compliance with usual safety standards. Otherwise, EMF exposure can disrupt electronic devices, medical tools and living tissues in general. This can be verified by electromagnetic compatibility (EMC) routines using equation (1). In the case of living tissues that exhibit biological thermal effects under EMF exposure, a particular heat transfer equation must be used; this is the bio-heat equation [45]. Compliance with safety standards guarantees risk-free conditions.
- In Section 2, we discussed the relationship between complexity and nonlinearity of interdependence of interactions. It should be noted that in electromagnetic procedures each of the phenomena involved might behave non-linearly, e.g. the relations of B and H via the permeability μ in (1), and between V and I via the nonlinear voltage drop ʊ in (2). Additionally, the coupling behavior could also be nonlinear, e.g. the relationship between the magnetic force F_{mag} and the mechanical movement X in the coupling of (1) and (2).
- Concerning the modeling of the equations governing the procedure, it can be noted that the functional phenomena considered, including intelligent materials, are those desired while the other phenomena are undesired. Regarding discretized methods like finite elements practiced in electromagnetic procedures, the coupling of equations can involve desired as well as undesirable phenomena. These methods are well suited to modeling energy conversion machines that are often involved in clean energy procedures, for example [46,47].
- In Section 4, we considered the notion of a strategy of reduced calculation time on the virtual side to allow rapid matching of the real-virtual couple. Certainly, even if the complete model is close to reality, it might take too long. In such a case, it is necessary to reduce this time while preserving accuracy. This will depend greatly on the nature of the procedure involved. Thus, such reduction only retains the attributes of the model, which mainly affect the procedure involved.
- A complex real procedure is adapted to its virtual mathematical model replica in a DT supervision tool involved in adaptive dynamic performance. The complex behavior of the actual procedure guides to its corresponding complex model. Such complexity could be attributed to weaknesses in computational resources, real-time simulation, or the need for many multiple simulations. This complex full model is not well suited for the adequate adaptive supervision required due to its excessive computational time. The latter could be reduced using digital assistance of different strategies; the most popular are model order reduction (MOR) and substitution or surrogate model (SM). The MOR aims to reduce the computational complexity of the virtual model, particularly used in the simulation of large-scale dynamic control procedures. This consists of reducing the dimension of the state space or the degree of freedom of the model. Thus, we obtain a reduced order model, which approximates the original full complex model. Such a strategy is often used when it is unlikely to enable numerical simulation of the full control model. A SM can be used as an approximate mathematical model of a given end result, which cannot be easily determined by measurement or calculation. This is substitution modeling, also called metamodeling, or emulation, which imitates the course of the simulation as faithfully as possible while requiring reduced calculation time. SMs are built with a bottom-up data-driven methodology and rely solely on input-output behavior and are also known as behavioral or black box modeling. Note that, in the case of a single variable, this approach will be a curve fitting.

6. Conclusions

This commentary aimed to analyze and discuss the mathematical coupling of interactions in complex procedures and their supervision in clean electromagnetic energy systems based on a review of the literature. The following concluding remarks can be summarized:

- The complexity of a real energy procedure regulates the complexity of its coupled virtual model, which sizes its behavior precisely.
- The strategy for reducing model calculation time is not universal. Saving the significant attributes of the energy procedure model is contrasting for each use and choosing a time reduction strategy depends on the specific demands and goals of the use.
- Matching exercise within a real-virtual pair allows both sides of the pair to be refined and permits to respond to their uncertainties.

Ethics Statement

Not applicable.

Informed Consent Statement

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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