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Strategies for managing models regarding environmental confidence and complexity involved in intelligent control of energy systems - A review

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Abstract. This assessment aims to analyze, illustrate, and examine the complexity and confidence problem associated with monitoring dynamic energy systems and managing them through model coupling and reduction. The confidence problem, which is related to the proximity of models to reality, can be reduced in general by considering neglected secondary domains by coupling their models to that of the main domain. Moreover, the complexity must be properly accounted for in the system models without decreasing the monitoring efficiency, which can be done through appropriate numerical model reduction techniques. In the article, after having posed the problem to be solved, we discussed and analyzed the automated procedures involved in energy systems. The notions of complexity and confidence in these systems are then illustrated and analyzed. In this framework, a complete coupled physical model reducing the confidence problem is then discussed and demonstrated. Model reduction strategies needed to optimize matching in automated procedures are then reviewed and analyzed. Finally, the pairing behavior of digital twins involving complex procedures is discussed and assessed, using a literature review. At the end of the paper, the case of electric and intelligent vehicles is discussed as an example of energy systems.

Keywords. Energy systems, smart control, dynamics; complexity, confidence, coupled models, online matching, model reduction.

1. Introduction

Modern energy systems often involve automated procedures. These procedures can be simple or composite. A simple automated process concerns a single component scheme while a composite one involves in general a multicomponent assembly. The behaviors of these procedures are linked to their environmental conditions. The analysis of such behaviors should account for phenomena involved in the setting of the procedure. Such analysis is often done through a coupled solution of mathematical representations of the procedure and the associated phenomena. In the case of a composite procedure involving several components, the behavior will be characterized by multicomponent-joined solutions of different components with their associated phenomena. In these automated procedures, following the latest integrated information technology and computer technologies, many opportunities for intelligent supervision are yet to come. These innovative tools will help real-time data and knowledgeable management in smart supervising. However, complexity and confidence stay main defies in such procedures.

We can characterize the two notions of complexity and confidence as follows. The complexity of a composite system denotes an intricate behavioral character resulting from the interaction of several components with interdependent behaviors; the degree of such interdependence relates the level of complexity. Moreover, the degree of complexity in a composite multicomponent system can be defined in terms of interactions [1]. These can be classified according to their increasing complexity into three types: simple, complicated and complex interactions. The first behaves directly or linearly, complicated one is linear and loosely coupled while complex interaction with tightly coupled links would be representative of the last type. The confidence involved in a system indicates how well an integrated assessment tool (measurement or modeling) represents its target or sight. Artificial inelegance and device knowledge can offer occasions to reduce largely the challenges of complexity and confidence problem. For instance, deep learning can be operated to enhance comprehending the supervision situation and further precisely forecast an upcoming difficulty or malfunction in a procedure sooner than it occurs, thus steering to fault-free procedure. Added defy in the evolution to smart and compliant mechanization could include persons in the ring that is human association tools.

The monitoring of energy systems is very concerned by the confidence associated with automated procedures. The impact of confidence problem becomes all the more important as the complexity of the procedure is higher. Improving the behavior of the system implies that these confidence problems are quantified and minimized. The quantification of confidence problem can be described as the practice of counting the confidence allied to actual physical quantities or their corresponding models. This is practiced with the aim of considering all appropriate causes of confidence problem and quantifying the impacts of individual sources to the whole confidence; see e.g [2, 3]. The quantification and minimization of confidence problem are essential in measurement practices (involving sensing, control, and data processing) and the mathematical modeling of systems and in particular, those with high complexity see e.g. [4-8]. Usual sources of confidence problem related to numerical models comprise confidence in the mathematical formulation of the models, confidence in the initial and boundary conditions, and confidence in the measurements used to determine the parameters in models.

The general representation of an automated procedure (simple or composite) is illustrated in figure 1. The behavior of such procedure is closely related to confidence problematic. These confidence problems involve sensors, control, data processing and model. The real time matching of observation vs. modeling in the procedure is directly affected by these confidence problems. The most important is this related to the model. The precision of the model in a matching practice poses a challenging deal concerning the matching swiftness. The more the model is simple the matching will be swift but continuously iterating. Contrary, for highly precise model the matching will be time-consuming with limited iterative character. The choice of the compromise of such challenge depends on the procedure complexity and used matching technology. Nevertheless, even if the amended model that account for procedure real environmental conditions, will be close to reality, it could be complicated and excessively time consuming. In such a case, we need a model reduction with preservation of precision to optimize the matching. This will depend on the nature of the concerned procedure. Thus, such a reduction retains only the attributes of the model, which mainly affect the procedure involved.

This paper presents an analysis and a review of the importance of confidence and complexities in automated procedures in general. First, automated procedures involved in energy systems are analyzed. Then, composite procedures and confidence involved in measured and modeled items are examined and assessed. In the case of models, the confidence problem quantification, amended models in energy procedures and supervision optimization via reduction of these models are studied and reviewed. Next, the strategies of model reduction, matching behavior and twins involving complex procedures are assessed and analyzed. Finally, we have considered the case of electric and intelligent vehicles as example of such energy systems and assessed the different aspects of the involved components with literature support.

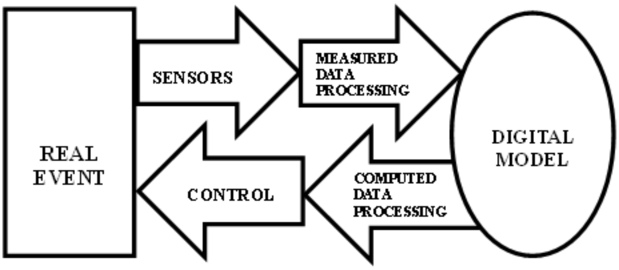

Figure1. Schematic representation of observation vs. modeling matching in an automated procedure

2. Problematic Positioning

Modern energy systems are essential applications in daily life. These systems systematically use intelligent automated procedures, which can be simple or composite depending on the system concerned. The supervision of these intelligent procedures generally uses the latest integrated computer and digital technologies available. These new tools smooth simultaneous data and experienced management in smart monitoring. An important characteristic of these digital tools is related to their capacity to replicate the physical assets of the system in real time. Such replication largely depends on the complexity of the system and the accuracy of the tool. Moreover, such a capacity for physical simulation based on numerical methods implies, to be precise, a significant computation time, in particular in temporal simulation. Such a calculation time can hardly meet the requirements of the numerical tool, which requires rapid matching in real time. Hence, it is required to construct compact models of precise and proficient conduct.

In the last paragraph, we encountered different notions affecting modern energy systems. On the one hand, intelligent automated procedures using online (fast) digital tools (accurate models). On the other hand, the complexity of the systems, the confidence of the models and the need to reduce the models for fast matching. This clearly illustrates the relationship of the notions: complexity, confidence, online matching and model reduction. These notions are related to complex systems, exact replicated physical models, fast online control of dynamic performance and timesaving reduced behavioral representations. The main challenge is to consider the complexity with a reduced confidence problem replica in an efficient dynamic matching procedure. The difficulty seems to be related to the need for an augmented (physical) model and a reduced (digital) model. Indeed, the increase and the reduction are not in contradiction because respectively the first plays on the physical accuracy while the second acts on the elimination of the superfluous in digital layouts.

3. Energy Automated Systems

Modern energy systems often use automated procedures to control and optimize the performance of these systems. These automated procedures use as input quantities ongoing values measured by sensors relating to specific operating variables and system parameters. However, in some situations, these measurements may be difficult or impossible. In this case, the estimate can be used for the variables or the parameters concerned. The control algorithms use the measured or estimated input quantities to work out feedback instructions for the control of the systems. The control algorithms as well as the estimators employ mathematical models characterizing the real system. The quality of the system model and the accurate estimation of the parameters play a vital function in the action of automated schemes. The execution of an algorithm on an implanted supervisor platform necessitates a simple model of the system. For this, one often achieves these operations offline to achieve judicious precision. For this, we can use computer-aided engineering (CAE) means based on whole models signifying the systems in their atmospheres. In such a circumstance, the matching of the modelled behaviors to the real ones would be fruitful. Nevertheless, the difficulty is that pairing cannot be immediate (on-line) with the procedure functioning. One of the energy fields most involved in automated systems containing simple or composite procedures is electrical energy and more generally electromagnetic energy. Various studies have proposed a compromise between model (estimator) accuracy and matching speed by implementing, more sophisticated algorithms, on specialized embedded controller platforms. For this, in automated systems, diverse kinds of observers, state filters and controllers are accessible as estimators. The robustness of the controller is reinforced by using adaptive approaches. Great-capability microcontrollers can expand controller board plan and software necessary for estimation, which iteratively goals the match instantaneously [9-16]. In addition, the complete model can be adapted by using model reduction with precision conservation strategies, see e.g. [17-20]. Indeed, complete models are essential to corroborate the features, operation and physical integrity of simple and composite procedures entangled in modern energy systems. The growth in the complexity of the models enlarges the computation time. Model reduction practices can advance a decrease in such time, while preserving enough accuracy. The spirit of model reduction is to maintain only the physical occurrences and amounts of importance from a model of high intricacy, permitting a humbler model that can (optimistically) be cracked more effectually. Subject to the nature of problematic and the domain of investigation, diverse model reduction approaches are available [21].

4. Complex Procedures

We have understood that the character of a physical scheme besides the confidence of the simulation process regularly make it tough to construct a faithful model and that we require a conciliation between the simulation accuracy and pairing rapidity in automated systems. These remarks are related to the enhancement of the pairing of models to their physical processes. Such an act is related to the potentials of the model and its communication with the physical entity. The significance of the model is linked with its aptitude to consider the different events implicated in the real process. The feature of the "physical-simulated" duo is connected to sensor indication, treating and command aptitudes.

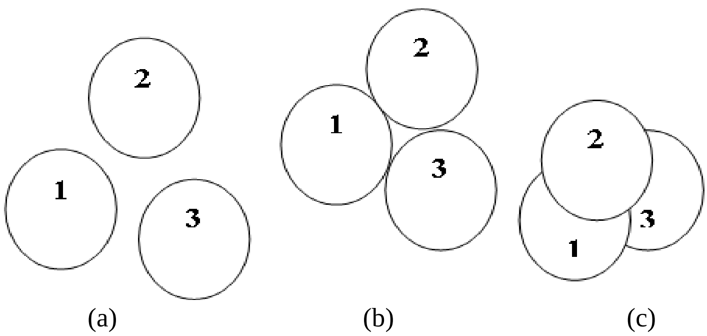

Figure 2. Schematic of interactions in composite procedures composed of several components (e.g. 3 in this figure). (a) simple, (b) complicated, (c) complex.

The burden of the enhancement of the pairing befalls exceptionally critical in the composite actions where the complexity relays to the different integrated constituents taking into account the physical events brought into play. As mentioned earlier, composite systems are composed of different components that behave in simple (linear), complicated (loosely coupled) or complex (tightly coupled) interactions. Figure 2 illustrates such interactions.

Note that complicated is different from complex. Complicated procedure does not change its behavior while complex procedure is adaptive. Thus, knowing the initial conditions in the first case permits to predict its outcomes whereas in the complex case, the same initial conditions can engender different outcomes, subject to the interactions of the elements in the system. Complex adaptive systems can be encountered in many situations involving artificial as well as natural systems, e.g. human brain that is the most complex structure in the universe. Complexity can be due to numerous participants, several organizational structures, or various steps that need to be monitored in a process. Complexity and complex systems are the object of many investigations see e.g. [22-25]. As mentioned earlier, the monitoring of these systems is closely related to their involved confidence. Confidence problem is the consequence of owning imperfect knowledge about an incidence or event, rendering it tough to control, plan, or predict a future outcome, which can often be disturbing. In automated systems these confidence problems concern measurements on the observation side as well modeling in the virtual side, see e.g. [26-28]. The next sections regard these two categories of confidence.

5. Confidence in Automated Procedures

Confidence involved in automated procedures are of two categories related to observation (measurement) and virtual (modeling).

The observable variables or parameters are connected to measurement involving sensors and data processing tools as well as estimators in case of quantities that meet measuring difficulties or impossibilities. The sensors characteristics depend of the sensing nature and the quality of sensors. The data processing tool reflects algorithmic treatment that depends on processing swiftness. The estimator is correlated to exactness of estimator type and its speed. Regarding the evaluation of the value of a measurement, it could be in terms of accuracy, which is a qualitative concept and corresponds to the proximity of the measurement and the real quantity of the measurable. On the other hand, one can evaluate the significance of a measurement in terms of confidence, which is quantitative and corresponds to a parameter associated with the result of the measurement, which characterizes the dispersion of the values that one could reasonably attribute to the measurable. This parameter can be e.g. a standard deviation or a width of a confidence interval. It generally includes several components assessed from the statistical dispersal or the assumed probability distributions of the results [4-8]. Concerning measurements, we can say that, the observation category of confidence can be evaluated and it appears mastered.

The modeling confidence is a subject of investigation. In the practice of link observation - modeling discussed earlier, we may encounter different circumstances concerning the type of the link itself, as well as the scenery of the phenomenon concerned and its behavior. The modeling side of the link may involve prediction, which may be practiced to solve difficulties concerning the problem of model confidence. Such confidence problem is affiliated with different notions such as volatility, inexactitude and changeability. Generally, confidence problem can be classified as arbitrary or epistemic. The first is associated with random variations, existing in natural variability, occurring in the world or possessing an external nature, while epistemic confidence is associated with an unknown, subsequent to a lack of knowledge, acting in the spirit or possessing an internal character. Thus, the epistemic or knowledge confidence problem can be decreased with the collection of additional data or by improving the models established on a better understanding of the objects concerned. On the other hand, random confidence problem in natural variations cannot be reduced by providing additional information. Therefore, improving the model implies that its knowledge confidence problems are quantified and minimized.

6. Managing of Models

6.1. Smartness Assumption Reductions and its Reversal

The coherence of a universal theory in a main scientific field originates of the situation of disregarding various fewer significant happenings existing in the physical sphere. Such assumptions compress and idealize existing reality. Generally, in application to real systems, these universal theories based on basic science might be incompatible with reality and not always immediately applicable. In such cases, it is necessary to adjust the model built on the theory of the principal field, by combining the secondary fields, neglected by smartness, in an adjusted model.

Consider an actual material event that could be denoted mathematically by the field A, which is the union of the functions B, C, D..., given by (1).

$$A : B(x, y) \cup C(y) \cup D(z) \ldots \quad (1)$$

$$B : B(x, y) \quad (2)$$

$$B' : B(x) \quad (3)$$

These functions link to diverse scientific fields. To model this actual problem, we usually have to reflect the diverse characteristics related to the different fields of science relating to the field A. On the other hand, often one field is more concerned with the problem than the others are, let us call it the main field and represent it by the function B, given by (2). In general, one tends to consider only this main domain to practice modeling through a smart universal theory. The coherence of such a theory requires idealized hypotheses leading to a simplified function B denoted B', given by (3). Consequently, when modeling an actual case using only the idealized main field theory, the outcome would regularly be erroneous. This is because of the restriction of two approximations. The first results from the neglect of influences from other domains (replacement of A by B) and the second results from the use of idealizing postulations (replacement of B-by-B'). In such a situation, to correct this condition, we must follow an inverse approximation method that allows reconsidering in the model all the neglected aspects resulting from the approximations used. It can be noted that, the reduction of the field A to a main domain signified by the function B as described above could operate in the same way on the functions C, D...

An example of energy systems illustrating the mathematical modeling in equations (1-3) could be the case of electromagnetic energy systems where (3) corresponds to Maxwell's equations while (1) concerns the coupling of electromagnetism with other fields such as mechanics, thermal… For more details, see e.g. [29].

Figure 3 illustrates a summary representation of the postulations applied to the field of a real setting resulting in an intelligent theory of the main field and its inverse. The latter shows how to use correctly the elegant theory by mathematical coupling to model the real setting.

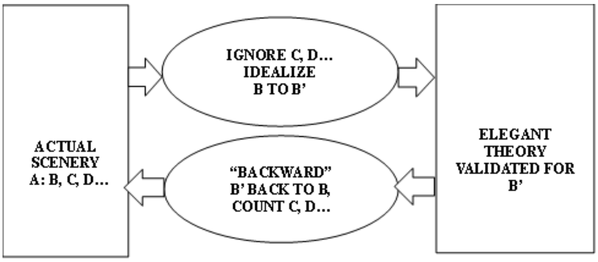

Figure 3. Representation of suppositions affected to actual scenery fields deriving to a smart theory of the principal field and its inverse, [29].
A real field, B principal field, C, D… inferior fields, B' main idealized field.

6.2. Amended Models in Energy Systems

As stated above, the diminution of knowledge confidence problem in models of energy systems involving composite automated procedures can be achieved through the improvement of these models. The closer these models are to reality, the better the adequacy of their observation-modeling link and thus increased supervision, behavior and performance.

This improvement of the model can be obtained by the coupling of the principal field theory usually used, with the theories governing the real environmental phenomena and commonly neglected in smart universal theories. Such a strategy of the complete model can be practiced generally in the different energy domains, see e.g. [29].

6.3. Optimal Supervision and Model Reduction

In automated procedures, supervision via the observation-model link must be optimal. Thus, the model must be sufficiently precise without taking a long time to execute. A complete coupled model is certainly close to real system behavior. Nevertheless, in case of model convolution, the execution will be tedious and long. Therefore, we need a trade-off between model accuracy and matching speed using algorithms that are more sophisticated.

Model convolution refers to specific properties of mathematical models taking place within a framework of scientific circumstances e.g. coupled complete models. These may be, for example, models that are over-parameterized in relation to the size of the data collected, models that are not intuitively comprehended because of their magnitude, or models whose size is intractable in terms of calculation. In each case, the complication impedes the regular means of analyzing the model. Model reduction techniques present a potential approach to solve the perpetual problem of model complexity by seeking to approximate the behavior of a model by constructing a simplified structure that preserves some degree of the capability of the initial one.

In such a case, the complete model can be adapted using a strategy for model-reduction with preservation of precision. Thus, such a reduction retains only the attributes of the model, which mainly affect the procedure involved. In this case, the field A, which is the union of the functions B, C, D... stated in the last section, would be replaced by the adapted reduced one A_r, see figure 4.

In the case of composite (multi component) system, one can reduce each component before unifying the system or the reverse depending on the nature of these components and the reduction methodology. The sensing and back control are performed individually per component while the model using sensed data to determine control indications is the unified model accounting for complexity nature of the components.

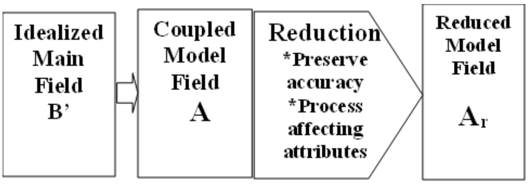

Figure 4. Illustration of the complete coupled model reduction with accuracy preservation limited to process affecting attributes.

6.4. Reduction Strategies

A valuable way in the design of composite systems is the numerical simulation of predictive dynamic models, which are generally of high order and expressed by a large number of ordinary differential equations. Such a high order could be due to the intrinsic system complexity or the partial differential equations discretization. Model reduction permits to obtain a lower-order model that approaches the behavior of the original model, while simplifying both computational analysis and realizing of the controller permitting to engender the desired behavior [18]. Three categories of model reduction can be dissociated and are detailed here.

The earliest model reduction techniques focused on the dynamics of structures that concern the deformations calculation, inside stresses or dynamic assets. Usual goals are the identification of natural frequencies or the calculation of frequency response functions. The mathematical models are essentially based on partial differential equations solved by discretization techniques, as e.g. finite element method (FEM). In this case, it is customary to subdivide the structure into components, on which the reduction is applied separately. Then, these component reduced-order models are joined to characterize the overall conduct. Different reduction methods have been developed in the case of structural dynamics; see e.g. [30, 31].

The model reduction techniques have also been employed in systems and control domain for the investigation of dynamical systems and the realization of feedback controllers. At this point, the goal of the controller design is to adjust the dynamics of the system to achieve the desired behavior, e.g. calm unstable systems, monitor a reference trajectory or eliminate outer troubles taking place in a system. These control policies are employed in a wide variety of problems, such as electrical and mechanical structures. These applications share the common point of dealing with systems characterized by inputs and outputs. More specifically, a number of actuators playing role of inputs, influencing the dynamics of the system and a number of sensors playing role of outputs are present in such applications. It is important to have a precise model of this input-output behavior. To enable the design of controller, which must be implemented in real time, model reduction is necessary. Moreover, the use of these lower-order models representing the initial model necessitates very precise methods of model reduction, where the conservancy of the significant belongings of the systems as stability is of big significance. Procedures of model reduction in the domain of systems and control hence target to approach the input-output conduct of a model of high-order. Balanced truncation is the method that preserves the stability of the model of high-order and delivers a mistake border, which gives a straight evaluation of the feature of the low-order model. Many works have been published in this domain; see e.g. [32-38].

Finally, model reduction numerical methods have been established in the field of arithmetical mathematics, which are often used in the design and investigation of huge electronic circuits; see e.g. [39-42].

Notice that, although the techniques in the three situations mentioned above principally manage the same model reduction question, the investigations in these three fields have been mostly settled individually.

The model reduction strategy most involved in the present contribution, relative to automated procedures involved in energy systems, is the one of the second category discussed above, namely, model reduction techniques in systems and control domain. This permits the investigation of dynamical behaviors and realization of feedback controllers.

7. Matching Behavior

We have seen that in case of automated procedures (section 3) we are in the presence of a pairing of observed quantities characterizing the real behavior of the procedure with a modeled behavior. The discrepancy between these observed and modeled behaviors is managed through an iterative process. The performance of these procedures is strongly linked to such a difference; the closer the observation-modeling couple, the higher the performance will be. The precision of each side of this pair is directly related to the notion of confidence. Thus, the overall performance of the procedure that depends on the iterative occurrence of matching will entail different confidence problem involving the two sides of the pair and the matching tool in between. As mentioned earlier, the different confidence involved in simple or composite automated systems are related to measurements, data processing, control and modeling (see Figure 1). These confidence problems are involved on the (actual) observation side, on the modeling side, and in the link between the two. The behavior of the system, which is linked to optimization (of system efficiency, performance, etc.), operating safety, etc., must reflect normal operation or degraded operation following a failure of the system. The matching performed in the system directly depends on the different confidences. The reductions of these for measurement, data processing and model allow the matching link to behave correctly and easily. The quality of such a link is governed by its swiftness and the deviation between the actual observation and the modeling output; the higher the rapidity and the lower the deviation, the better the link performs.

8. Twins Involving Complex Procedures

The predictability and controllability of complex dynamical systems are challenging as shown in the last sections. Thus, managing the involved compound procedures can be achieved by practicing the Internet of Things (IoT) that exposes powerfully in the physical area through, straight instantaneous data gathering, or computer-aided engineering (CAE) tools based on fulfilled models signifying the systems in their surroundings, which centers entirely on the numerical ground.

Nevertheless, it is indispensable to appease and contain the inappropriate and unwanted conducts that arise in these complex procedures. Accomplishing such, an objective necessitates a matching observation-model twin exercised in the relevant procedure [43]. An intelligible picture of such a matched twin can still be represented by figure 1. Such a twin diverges from both IoT and CAE by centering on equally the physical and numerical scopes. This twin requests the practice of detection on the observation side, calculation on model side and data processing and control link between the two sides. Detection concerns the different sensor identifications. The calculations implicate optimization, simulation, prediction, diagnosis... These procedures can utilize learned gathered data adjunct to sensor information. The link observation-model is bidirectional. The observation side delivers sensor quantities in treated form to the model side while the last directs processes and control data to the observation side.

The twin of figure 1 relates to the Digital Twin (DT). The DT notion was primary presented in 2002 by Grieves M. [43]. It is typified by an advantageous two-way exchange between the virtual and physical circles. The three components of a DT are a matched observable, a real-time virtual digital element, and their sensory, processing, control, and matching links. The physical part regulates its conduct in real time consistent with the advices made by virtual part, while the virtual side properly replicates the real situation of the physical part. Thus, the DT proposes a smart association of the real and virtual sides [44]. This is an occurrence of a real-time bidirectional joined matching process. Observation revises the virtual error and the virtual side adjusts the observed data. This iterative progression directs to a further smart association. The DT concept is largely used for fault identification, predictive maintenance, performing analysis and merchandise design [45]. This interests different grounds and advanced industrial strategies such as machinery manufacturing, automotive transport, aerospace and aeronautics, energy and utilities, healthcare and consumer merchandises. Numerous works have been published in this domain involving different applications; see e.g. [46-58]. Recently DT have been used in a frame of human cooperative use, see e.g. [59].

An important characteristic of the digital twin is its aptitude to replicate the physical belongings of the article online, as discussed in section 2. However, physical replication is based generally on mathematical methods, which entails great computation time, particularly in time-domain simulation, and therefore can scarcely come across the requirements of DT, which needs fast matching in real time. Therefore, there is a need to construct precise and effective performance models. This may be built by data-driven regression/interpolation methods, such as kriging, and machine learning, which pose the problem of requiring a huge volume of simulation or measurement data. The model reduction strategy for systems and control described in section 6.4 allows creating compressed conduct models based on simulation data and system a priori information. Such a solution come to be one of the encouraging methodologies to achieve the vital objective of DT for numerous industrial requests [17, 18].

9. Discussion

In this contribution, the followed analysis and evaluation of roles of model coupling and reduction processes regarding complexity and confidence in the dynamics of intelligent control pairing have exhibited the importance of different elements. At this point, various points are worth remarking on:

We have exploited the nature of the observation - modeling (or real - virtual) link, in different places in this work. This involves offline and real-time matching practices. In the case of smartness assumption reductions, the offline matching practice of the link is usually used for the management and ruling of elegant theories. Real-time pairing of this link concerns autonomous automated systems and complex procedures [60].

Automated systems use mathematical models in their control to represent complex procedures as in the case of DT. The demand for improved predictions and increased accuracy necessitates the evolution of these models to ever-increasing size and complexity. Such models often connect subsystems that can represent various natures, scales of time and space. Inferred demands on computing resources can easily exceed practicability limits, placing the need for model reduction techniques. Model reduction can be expressed succinctly as the process of replacing a large, complicated mathematical model with a lighter, simpler (but still accurate) one. Note that the path from smart theories to coupled models corresponds to including neglected physical phenomena approaching reality, while the one from complete to reduced models concerns neglecting numerical (arithmetic) superfluous time-consuming computations. This last permit optimized supervision through swift matching in the control.

Application on the case of electric and intelligent vehicles: In the present contribution, different topics have been analyzed namely: confidence, complexities, automated procedures, energy automated systems, complex procedures, amended models, supervision optimization, reduction of models, matching behavior, twins involving complex procedures… Each of these themes has been supported by corresponding literature. We have considered an application category uses or can use most of these topics. This is the case of electric and intelligent vehicles exhibiting advances in modeling, dynamics, intelligent control, and diagnosis in automobile engineering. This involves different features such as vehicle condition monitoring, battery management systems, autonomous navigation control, electronics and electric drive systems, driver assistance systems, electric grid concerns and health safety. Such category of applications reflects a composite (multicomponent) system involving smart automated procedures that require precise and reduced models. Examples involving mainly dynamics control are present in literature see e.g. [61-64]. Cases implying energy transition and integration in power systems can be found e.g. [65-69]. Regarding battery charging management, several works are available; see e.g. [70-77]. Considering renewal energy capacities in charging control, see e.g. [78-80]. Concerning automotive electric motor optimization and diagnostics, see e.g. [81, 82]. Regarding applications using wireless battery charging for static, on road and underwater cases, see e.g. [83-87] and health safety control related to these technologies, see e.g. [88, 89].

10. Conclusions

The intentions of this contribution were the analysis, investigation and evaluation of the complexity and confidence associated with the monitoring of dynamic energy systems and their management by the techniques of model coupling and reduction. The following points summarize the outcome of the article:

Automated procedures involved in energy systems have been analyzed and reviewed. The notions of complexity and confidence in these systems have been illustrated and evaluated.

The reduction of confidence problem and the consideration of complexities have been analyzed and studied. These relate primarily to the exactness and numerical nature of the system model used in the numerical control. A realistic amended-model of the system concerned with a reasonable execution time can allow this. Such an amended-model in the case of a simple automated procedure would be a physically coupled and numerically reduced (PCNR) model. In the case of a composite procedure, the amended-model would be the result of unified components (each is PCNR). The swiftness of matching of the digital control has been evaluated and analyzed. Such speed is closely related to confidence and complexity and therefore requires exactness and reduced execution time of the system model. This involves the evaluation of adequate model reduction strategies that preserve accuracy and eliminate unnecessary numerical calculations.

The strategies to be practiced in the coupling and the reduction of the system model as well as the corresponding speed of control matching mentioned in the last point seem closely linked to the nature of the procedure involved. It is a question, for a given procedure, of choosing which physical phenomenon must be included in the coupling and which numerical part must be suppressed in the reduction. A full assessment of these issues requires further investigation in future work.

At the end of the article, we have chosen to consider the case of electric and intelligent vehicles as an example of the energy systems investigated in this contribution. An analysis of such case and evaluation aided by a review of the literature were presented in the discussion section.

Conflicts of Interest: The author declares no conflict of interest.

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