ACADÉMIE
DES SCIENCES
INSTITUT DE FRANCE

# Comptes Rendus
# Physique

Adel Razek

**Matching of an observed event and its virtual model in relation to smart theories, coupled models and supervision of complex procedures—A review**

Published online: 2 May 2024

**Part of Special Issue:** Energy in the heart of EM waves: modelling, measurements and management
**Guest editors:** Emmanuelle Conil (ANFR, France), François Costa (ENS Paris-Saclay, Université Paris-Saclay, Université Paris-Est Créteil, France) and Lionel Pichon (CNRS, CentraleSupélec, Université Paris-Saclay, Sorbonne Université, France)

https://doi.org/10.5802/crphys.184



CENTRE
MERSENNE

*The* Comptes Rendus. Physique *are a member of the Mersenne Center for open scientific publishing*
www.centre-mersenne.org — e-ISSN : 1878-1535

ACADÉMIE DES SCIENCES
INSTITUT DE FRANCE

*Comptes Rendus. Physique*
Published online: 2 May 2024
https://doi.org/10.5802/crphys.184

Review article / *Article de synthèse*

Energy in the heart of EM waves: modelling, measurements and management / *L'énergie au cœur des ondes électromagnétiques : modélisation, mesures et gestion*

# Matching of an observed event and its virtual model in relation to smart theories, coupled models and supervision of complex procedures—A review

*Appariement d'un évènement observé et de son modèle virtuel en relation aux théories intelligentes, aux modèles couplés et à la supervision de procédures complexes — Bilan*

**Adel Razek** [a]

[a] Group of Electrical Engineering – Paris (GeePs), CNRS, University of Paris-Saclay and Sorbonne University, F91190 Gif sur Yvette, France

*E-mail:* adel.razek@centralesupelec.fr

**Abstract.** This contribution aims to illustrate the nature of the observation–modeling (or real–virtual) link, the importance of the exact model (or coupled model) in the matching involved in this link and the use of this link in the supervision of complex procedures. This involves offline and real-time matching practices. The offline case is mainly about the management and ruling of elegant theories and computational tools mimicking physical paradigms. Real-time pairing notably concerns natural phenomena, autonomous automated systems and complex procedures. The paper assesses, analyzes and discusses the different elements mentioned. This is aided by a literature review.

**Résumé.** Cette contribution vise à illustrer la nature du lien observation–modélisation (ou réel–virtuel), l'importance du modèle exact (ou modèle couplé) dans l'appariement impliqué dans ce lien et l'utilisation de ce lien dans la supervision de procédures complexes. Cela implique des pratiques de mise en correspondance hors ligne et en temps réel. Le cas hors ligne concerne principalement la gestion de théories élégantes et d'outils informatiques imitant des paradigmes physiques. L'appariement en temps réel concerne notamment les phénomènes naturels, les systèmes automatisés autonomes et les procédures complexes. Le document évalue, analyse et discute les différents éléments mentionnés. Cela est assisté par une revue de la littérature.

**Keywords.** Matching, Coupled models, Electromagnetic systems, Complex producers, Supervision.

**Mots-clés.** Appariement, Modèles couplés, Systèmes électromagnétiques, Producteurs complexes, Supervision.

**Note.** This article follows the URSI-France workshop held on 21 and 22 March 2023 at Paris-Saclay.

*Manuscript received 26 May 2023, revised 17 January 2024, accepted 19 March 2024.*

## 1. Introduction

Cognitive inference or virtual modeling can account for the observation of an object, phenomenon or procedure. Pairing or mirroring an observable and its virtual image has been, and still is done in many natural and man-made situations. Humankind, other creatures and natural elements often exercise the practice of observation, experience or sensory manipulation. At the same time, from this practice, they will eventually use deductive (or mimesis) skills to manage their evolution, self-protection, comfort, and survival. The activity of deduction associated with observation is one of the first natural duties born in the world. Deduction, prediction, or reasoning (modeling) associated with observation may be encountered in inherent natural events or manufactured procedures. Such a couple often works according to a process of pairing or imitation. For example, in nature, based on observation, cases of mimetic simulation (imitation strategy) are very frequent allowing camouflage [1]. This permits creatures to blend into their surroundings. This could involve simple matching or dynamic (adaptive) matching.

Both cases of link observation–modeling involving offline and online matching can be used in distinct matching categories. The offline one can be practiced in managing universal elegant theories involving their validation, explanation and unification. The online matching procedures of the link observation–modeling are practiced in various natural processes and artificial modern applications related to the supervision of automated and complex systems. In these applications, we need to reduce the involved uncertainties to achieve an optimized supervision. Such reduction is mostly needed in the virtual side of the link. Thus, we need accurate realistic system models, which can be obtained by reintegrating neglected items committed in idealizing for elegance of theories. Such coupled models permit optimized matching of the link observation–modeling. We see that the matching in the link is closely associated to elegant theories and coupled models, respectively for offline theories managing and online systems supervision.

Indeed, the foundation of basic research is built on elegant and consistent theories, which is essential for science. Let us illustrate the notion of elegance in the theories that belong to fundamental science. When a theory or model clearly and directly describes a phenomenon, it is said to be elegant. Additionally, an easy-to-understand enterprise can capture a lot of information and answer many questions. Therefore, the definition of elegance as simplicity plus greater capacity seems fair. Note that this last statement is valid only when the theory is applied in its strict scope. One of the most famous elegant unified theories is Maxwell's set of equations [2]. The case of Maxwell's equations illustrated the interest of the concept of elegance. However, later in this article in the application to electromagnetic systems, we will see that in real systems, Maxwell's equations could not always be applied immediately and such elegance could conflict with real applications. In such cases, one must make a volte-face from elegance to reality by reconsidering the corresponding committed approximations. We are therefore inclined to modify the model based on the theory of the main field, by combining the secondary fields in a modified coupled model [3]. Such a modified model resulting from "retrograde postulations" paradoxically seems to represent the real context. Note that coupled models belong to applied science.

Many recent innovative technological processes use the concept of matching physical (observable) operations with their (virtual) mirror models. Matching depth is closely related to the fidelity of the virtual model to the real physical object. Such consistency implies the nature and ability of the model to take into account the variation of the physical element due to its operational and environmental conditions [4]. Therefore, a complete model taking into account all the phenomena governing these conditions becomes necessary and the model uncertainty involved in such a circumstance will be of knowledge type. Currently, in very promising fields, where the large number of creations and the growing importance of digital components in automated assemblies offer an opportunity to reach higher levels of production [5]. The practice of digital technologies allows the virtual projection of products and processes [6]. The combination of physical and virtual elements can be achieved through the concept of matching physical operations with their mirror models—digital twin (DT). DT is gradually being studied as a means of improving the functioning of physical units by taking advantage of the computational practices made possible by those of virtual pairing. Bidirectional links feed data from the physical element to its virtual image, and process it from the latter to the physical element [7]. This matching sequence (pairing) is a kind of mirroring of real and virtual elements. The virtual one allows various specific tasks of simulation, test, optimization… [8]. Since Michael Grieves introduced the concept of digital twins in 2002, which has quickly taken hold in various fields; the number of publications on its applications has increased significantly.

This contribution aims to illustrate the nature of the observation–modeling link and its relation with elegant theories and coupled models. First, we analyze the role of this link in the managing of elegant universal theories. Then we discuss the relation of these smart theories and coupled models. At the last part of the paper, we illustrate the importance of coupled models in the real-time matching involved in this link and its use in the supervision of complex procedures.

## 2. Characteristics of the link observation–modeling

This section aims to examine how the two elements of observation and theory each support and mutually form a duo. Thus, we examine how they are complementary and evaluate their actions in the management of universal theories involving validation, explanation and unifying capacities. Finally, we discuss advanced computational tools mimicking the physical paradigms ruled by the duo. All the observation–theory duo activities discussed in this section fall under offline matching practices.

### 2.1. *Managing of smart theories*

#### 2.1.1. *Observation and theory complementarity*

Observation or theoretical modeling can be self-ruling in areas of investigation that are consistently seen as standards. However, in widespread cases, we use the two items in a complementary way. Therefore, yet in a domain that customarily necessitates observation, it is generally not autonomous and it requires modeling for further investigation. Structural research in social sciences is a typical example in this category; see e.g. [9], in addition, in a field currently requiring theoretical modeling, it is not regularly either autonomous and it requires to be validated by observation, simply to be reliable [10], as we will see in the next lines.

#### 2.1.2. *Validating or invalidating a theory by observation*

In general, a theory is only thought to be established after it has been verified by observation. Furthermore, such a theory stays true until inconsistency with another observation.

**Validation of the theory of superposition states in quantum mechanics.** Considering the case of the "theory of superposition states" in quantum mechanics proposed by Schrödinger in 1926 [11], (Nobel 1933). In this theory, the wave function provides the probability of locating a particle at a specific position. Wineland's ion traps [12] and the cavity quantum electrodynamics of Haroche [13] validated this theory a little before 2000 (Nobel 2012: for revolutionary experimental methods, which make it possible to measure and manipulate individual quantum systems). It was only after such validation that this theory was established until a possible future invalidation.

**Partial invalidation of the treatise of JC Maxwell by the Hall effect.** Concerning the "Hall Effect" proposed by Hall in 1879 that resulting from an experiment; it concerns the relation between the force and the current in a conductor. It invalidates part of the "treatise on electricity and magnetism" proposed by Maxwell in 1873 [14]. Hall revealed and experimentally confirmed in his thesis work, the effect of force on current (distribution) in a conductor immersed in a magnetic field [15]. Maxwell thought there was no such effect.

#### 2.1.3. *Observation confirmed and explained later by theory*

One can meet the situation of first reaching a finding from experiments and then establishing the theory explaining and confirming such discovery. Generally, we come across such a situation in a "serendipity condition": we find something while looking for another. A typical illustration is the revealing of the superconductivity phenomenon by Kamerlingh Onnes (1853–1926), (Nobel 1913: for his investigations on the properties of matter at low temperatures which led, inter alia, to the production of liquid helium) [16]. In this context, he was studying the problems connecting to the effects of low temperatures on electronics. He could not imagine the phenomenon he observed. All the theories confirming and explaining the superconductivity phenomenon followed his discovery.

#### 2.1.4. *Generalizing and amalgamating observations by a theory*

Several characteristics can distinguish intelligence of theories such as enhancement, generalization, and fusion. An example of such intelligence can be seen in Maxwell's equations, which are an illustration of the highest elegant composite theories. These equations originated by James Clerk Maxwell (1831–1879) incorporate an association of three laws that are obtained experimentally, discovered by three of his predecessors. They are Carl Friedrich Gauss (1777–1855), André-Marie Ampère (1775–1836) and Michael Faraday (1791–1867). The unification of Maxwell's equations was possible only because Maxwell remarked how to progress from the three experimental laws, introducing into one equation a missing link, the announced displacement current, the occurrence of which guarantees the consistency of the integrated organization [2, 14].

### 2.2. *Innovative computing tools imitating physical paradigms*

Neuromorphic and quantum computing technologies are two constructed tools based on imitations of physical systems. These two modeling tools originate straight from two paradigms belong to neurosciences and quantum physics.

#### 2.2.1. *Neuromorphic computing*

The brain is an exceptionally intricate organization that performs tasks much quicker than the swiftest digital computers. Neuromorphic computing uses inspired models of the brain built on biologically replicated or artificial neural networks. Neuromorphic computers can perform complex calculations quicker, with greater power efficiency and lesser size than traditional architectures. They have the capacity to expand trained real-time learning algorithms to work online like real brains. This showed potential due to the similarities of biological and artificial neural networks (BNN and ANN) [17]. The rising request of deep learning and neural networks has stimulated a sprint to advance artificial intelligence (AI) hardware devoted to neural network calculations [18]. These tools are broadly operated in optimization, diagnostics, images, machine learning, AI, etc.

### 2.2.2. *Quantum computing*

The notion of states in quantum mechanics is the base of "quantum computers", a term created by Richard Feynman [19]. A typical computer uses transistors to process information in sequences of zeros and ones (binary mode). A quantum computer uses qubits according to the rules of quantum mechanics connecting to particle states. For a qubit, a particle can be in several states simultaneously, as well, a different phenomenon affects particle states called entanglement. This means that when two qubits in a superposition meet; signifying the state of one depends on the state of the other. Due to these phenomena, a quantum computer can achieve 0, 1, or both states at the same time for a qubit or a qubit entanglement. Thus, an n-qubit quantum computer can work instantaneously on the 2n possibilities; however, a standard computer with n bits can only operate on one of these 2n possibilities at a time. Therefore, the former gives us more processing power. Scientists agree that quantum computers are theoretically exponentially faster and much smarter at cracking codes that are apparently unfeasible for classical technology [20, 21].

## 3. Idealized smart theories and coupled models

This section aims to analyze and discuss the characteristics of elegant theories and realistic coupled models. Often, the notion of elegance belongs to the philosophy of science. On the other hand, in the present article we specify that the use of the term of elegance of theories concern fundamental sciences whereas that of coupled models concerns applied sciences. Let us clarify the notion of elegance in the theories of fundamental sciences. When a theory describes a phenomenon in a clear and direct way, it is said to be elegant. Additionally, an easy-to-understand construct can provide a large amount of information and answer many questions. Therefore, the definition of elegance as simplicity and greater capacity seems right. Note that this last statement is only valid when the theory is employed within its strict scope of application.

### 3.1. *Smart theories and postulations*

Let us consider a real physical problem which could be represented by the field $A$, which is the union of the functions B, C, D... which depend on the variables $x, y, z\dots$. Each of these functions relates to a different domain of science. On the other hand, often a domain is more concerned by the problem studied than the others are, let us call it the main domain and represent it by the function B in (1). If we allow that the main domain B can represent the real problem, Equation (2) will give this approximation $A_1$. Moreover, founding coherent and elegant theories usually requires postulations that compress and idealize the real context resulting in $A_2$ given by (3).

$$A: \ \mathrm{B(x,y)} \cup \mathrm{C(y)} \cup \mathrm{D(z)} \dots \tag{1}$$

$$A_1: \ \mathrm{B(x,y)} \tag{2}$$

$$A_2: \ \mathrm{B(x)} \tag{3}$$

Note that the validation of this elegant theory given by $A_2$, which allows its foundation, must also be done under these postulation conditions.

Therefore, when we model a real problem using the main domain idealized theory, the result would often be erroneous. This is due to committing two approximations. The first is relative to overlooking the other domains influences (replacing $A$ by $A_1$) and the second is due to the use of idealizing postulations (replacing $A_1$ by $A_2$). The more these two approximations are unfounded vis-à-vis the real setting, the obtained results will be far from the reality. In such a case, in order to adjust this situation, we have to track a reverse procedure that to re-integer in the model, via coupling, all the ignored aspects subsequent to the used approximations. Concerning the reduction from expressions (1)–(3), one can study a given problem from different aspects corresponding to different reductions involving different approximations. This depends, for a multi-domain problem, on the investigated domain. For example, we will consider a problem involving thermal and biological domains. When studying thermal performance, one may tend to introduce biological approximations for reduction and reciprocally.

### 3.2. *Revised coupled models and solution strategy*

The reverse procedure mentioned in the last section will go through a kind of revised model comprising the main theory associated with the other theories involved and reintegrating into the model all the characteristics ignored in the idealizing action. In general, coupled problem schemes involve the mathematical solution of equations governing different natural or artificial phenomena belonging to distinct branches of the theoretical sphere. The nature of the behaviors of these phenomena and their interdependence as well as the proximity of their temporal evolution (time constants) are directly linked to the approach of solving the corresponding governing equations. Each of these behaviors can be linear or non-linear and have a low or high time evolution. Moreover, these behaviors can be independent or interdependent, which may or may not be linear. At one extreme, we have the case of independent linear behaviors with very distant time constants. In this case, we can solve the governing equations individually. At the other extreme, we have the case of nonlinear and, nonlinearly interdependent, behaviors with very close time constants. In this situation, we need a strongly coupled simultaneous solution of equations. Between these two extremes, the equations can be solved in consecutive progression mode by iteration according to the severity and the degree of complexity of the behaviors.

Moreover, in general, the nature of the source, the behavior of the matter and the geometry concerned in the real problems are more complex than, those envisaged in a smart theory. Therefore, the spatial and temporal behaviors of the different variables in the corresponding equations are also more complicated compared to elegant theories. Such a complex system of equations does not allow analytical solutions. In order to apply the theories correctly, it is often necessary to consider a discretized form in space and time of the equations. In this case, the theories will operate locally in finite discrete domains for which the global assembly solution will operate in the discretized time domain. Spatial local non-linearity is considered by iterative procedures.

### 3.3. *Case of electromagnetic and energy conversion systems*

For a better understanding of the problem addressed in the last section, we will consider an application in the field of electromagnetic systems (EMS) including energy conversion drives. These are present in many societal applications such as mobility, health, security, communication, etc. In these systems, the intelligent management, conversion and supervision of energy involve the use of an accurate realistic representation of the arrangement concerned. A revised realistic coupled model achieves this goal through its use in system design, optimization, and control. The main field in such a case is electromagnetic (EM), which is governed by Maxwell's equations. However, EMS generally behave in four territories: electrical, magnetic, mechanical and thermal.

### 3.3.1. *Maxwell equations*

This system of equations can be formulated mathematically in different forms depending on the problem under consideration. One of the most common is the basic full-wave electromagnetic formulation given by:

$$\nabla \times \mathbf{H} = \mathbf{J} \tag{4}$$

$$\mathbf{J} = \sigma\mathbf{E} + \mathrm{j}\omega\mathbf{D} + \mathbf{Je} \tag{5}$$

$$\mathbf{E} = -\nabla \mathrm{V} - \mathrm{j}\omega\mathbf{A} \tag{6}$$

$$\mathbf{B} = \nabla \times \mathbf{A} \tag{7}$$

where **H** and **E** are the magnetic and electric fields, **B** and **D** are the magnetic and electric inductions, **A** and V are the magnetic vector and electric scalar potentials. **J** and **Je** are the total and source current densities, $\sigma$ is the electric conductivity and $\omega$ is the frequency pulsation. The symbol $\nabla$ is a vector of partial derivative operators, and its three possible implications are gradient (product with a scalar field), divergence and curl (dot and cross products respectively with a vector field). The magnetic and electric behavior laws respectively between **B**/**H** and **D**/**E** are characterized respectively by the permeability $\mu$ and the permittivity $\varepsilon$.

The solution of Equations (4)–(7) permits to determine in a system the concerns of electromagnetic fields for a frequency pulsation accounting for the magnetic materials behaviors through the permeability, for eddy currents in electric conductors through the electric conductivity and for behavior of dielectrics through the permittivity. Often, EMS involve other fields than EM. In some cases, the influence of these other fields could be negligible and it will be then possible to solve the problem correctly with only the Maxwell's equations. In general, to model an EMS we need to account for other fields in addition to EM field through the coupling of the corresponding governing equations. As mentioned before, EMS behave under four phenomena: electrical, magnetic, mechanical, and thermal. The first three have small and relatively near-time constants while the thermal phenomenon has a relatively higher time constant. The different mixtures of these phenomena can be classified into causal (system behavior), integrated (electrical and magnetic) and intrinsic material (functional). The last mainly concerns intelligent materials such as magnetostrictive, electrostrictive, shape-memory, thermoelectric….

### 3.3.2. *Coupling and solution of equations in EMS*

The solution of the equations of the events involved must take into account different specifications. The nature of the behavior of the system concerned, involves analyses either in the frequency domain or in the time domain. The fact that EMS often have complex geometries and involve materials with nonlinear laws of behavior implies going through a local distribution of variables such as, fields, potentials…. For this purpose, we use 2D or 3D discretized geometric cells, with conditions defined on the boundaries of the discretized domains, see e.g. [22, 23]. The above-mentioned categories of couplings are detailed as follows.

**Integrated coupling.** Generally, in EMS the current is delivered by a voltage source through an external electric circuit. The general relation between the voltage $v$ and the current $i$ in the circuit is given by:

$$v = 1/C \cdot \int i\,\mathrm{d}t + ri + L \cdot \mathrm{d}i/\mathrm{d}t + \mathrm{d}\Psi/\mathrm{d}t + \mho \tag{8}$$

In this expression $r$ is the total resistance of the circuit, $L$ a linear inductance, $C$ a capacitance, $\mho$ a non-linear voltage drop (e.g., a diode) in the electrical circuit and $\Psi$ the implied flux linkage.

This circuit equation should be solved coupled with the EM equations. Therefore, the equations to solve are (4)–(8). This coupling between the EM domain and the external electric circuit is particular regarding other couplings with other domains than EM because it represents a "correction" inside the EM domain. We call it integrated coupling. Generally, the coupling of EM domain with the external electric domain needs simultaneous strong solution of the equations due to non-linearity of behaviors and closeness of the magnetic and electric time constants, see e.g. [24].

**Causal couplings.** This class of couplings is related to system behavior. Typical situations in this category are the EMS that governed by EM domain, where the operation, the source or the outcome is directly related to another domain. Most EMS related to energy conversion stand in this category; for instance, the mechanical source or outcome respectively in electric generators, e.g. [25] or motors e.g. [26]. These cases may involve behavioral alterations in the EM and other areas modified by each other. This happens when the behaviors are interdependent. The solution of the equations for a given EMS would be separate, iterative or strongly coupled, as mentioned before, depending on the severity of the behaviors.

*EM and mechanical coupled problem.* We consider the case of an EMS where beside EM the mechanical domain is involved in forms of displacement or deformation. Let us consider the example of the typical electromagnet given in Figure 1, which is a characteristic EMS involving electro–magneto–mechanical aspects permitting to illustrate the consideration of these different domains [27]. It consists of a stationary part constituted of non-conducting magnetic material ($\mu$) and a mobile armature made of conducting magnetic material ($\mu$, $\sigma$). A coil fed by a voltage source excites the stationary part. The mobile armature is connected to a spring, a damper and an external force. The equations governing such a system are:

$$m \cdot \mathrm{d}^2X/\mathrm{d}t^2 + c \cdot \mathrm{d}X/\mathrm{d}t + kX = F_{\mathrm{mag}} + F_{\mathrm{ext}} \tag{9}$$

$$\mathrm{d}\Psi/\mathrm{d}t + rI = U \tag{10}$$

In these equations, $U$ is the source voltage and $I$ the current in the exciting coil. $X$ is the displacement, $F_{\mathrm{mag}}$ and $F_{\mathrm{ext}}$ are the magnetic and external forces, $m$, $c$ and $k$ are respectively the mass of the moving object, the damping coefficient and the stiffness of the spring. It may be noted that (10) is a particular case of (8).

We consider for example in the system in Figure 1 a step source voltage in the exciting coil. The unknown variables are the current $I$ across the coil and the displacement $X$ of the mobile armature. The magnetic linkage flux $\Psi$ and the magnetic force $F_{\mathrm{mag}}$ generally could be nonlinear function of the magnetic saturation and the mechanical motion. To solve the problem we have to consider Equations (4)–(7) with the mechanical and circuit equations (9)–(10). Generally, the coupling of EM domain with the mechanical domain needs simultaneous strong solution of the equations due to non-linearity of behaviors and closeness of the time constants.

*EM and thermal coupled problem.* We consider the case of EMS where in addition to EM the thermal domain is present in the form of heating production [28] or resulting undesirable heating [29]. Heat production by means of EMS can be magnetic induction heating by eddy currents in conducing metals owning high conductivity or electric induction microwave heating in dielectric materials possessing high permittivity [30]. The coupling of EM and thermal domains involves phenomena with very different time constants. Moreover, the problem may include nonlinear behaviors and/or variables that are interdependent. Here we need a weak separately iterative coupling.

**Material intrinsic couplings.** This class of couplings is relative to functional nature regarding material intrinsic interactions. These concern mainly smart materials that each linking two phenomena: magnetostrictive (magnetic–mechanic), electrostrictive (electric–mechanic), shape-memory (thermic–mechanic), and thermoelectric (thermic–electric).

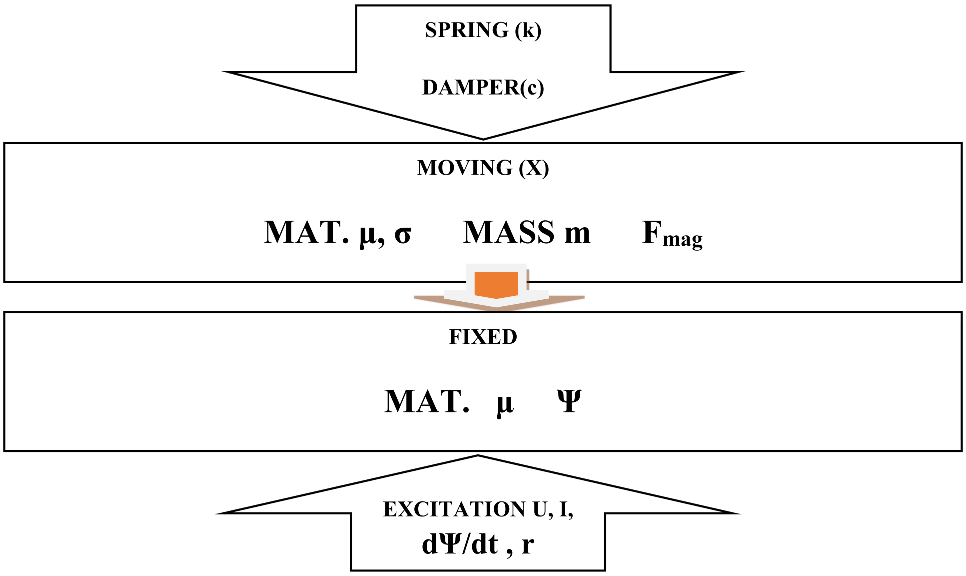


**Figure 1.** Schematic of an electromagnet involving electro–magneto–mechanical aspects [3].

The couplings in these cases relate to two groups. The first reflects linear behavior (electrostrictive) and/or very different time constants (shape-memory, thermoelectric). In this case, we can practice separate solutions or coupled iterative solutions for respectively independent or interdependent behavior [31, 32]. The second concerns non-linear behavior and/or close time constants (magnetostrictive). In function of the complexity of the nonlinear relationships, we use strong coupling or multiscale methodologies [33, 34].

#### 3.3.3. *Supervised energy conversion systems*

Energy conversion drives are frequently used in a wide range of applications ranging from small household appliances of a few watts to heavy industrial needs in megawatts, including mobility, medical, robotics applications .... These drives are supervised in several ways depending on the nature of the application in terms of required accuracy and required response time, ranging from slow to instantaneous; see e.g. [35–37]. In any case, we need the most accurate model of the drive involved in the control, which allows efficient and robust supervision. These energy conversion devices can be involved in simple automated systems or in complex supervised adaptive and dynamic procedures. This topic will be discussed in the next section.

## 4. Online matching of the observation–modeling pair

In Section 2, we surveyed the virtues of offline observation–modeling pairing. This duo is actively involved in many natural and artificial processes operating in online (real-time) pairing mode. This concerns both simple automated systems and complex procedures.

### 4.1. *Automated procedures*

Automated systems are used in various fields related to energy, industrial manufacturing, mobility, health .... In various automated procedures, sensors are commonly used to determine specific operating variables and system parameters. However, in some situations, estimation can be used for variables or parameters that are difficult to measure. Accurate parameter estimation plays a crucial role in the operation of automated systems. The implementation of an estimation algorithm on an embedded controller platform requires the simplification of the mathematical model of the system. That is why we often have to do this estimation offline to get reasonable accuracy. For this, one can use Computer Aided Design (CAD) tools based on complete models representing the systems in their environments (see Section 3.3). In such a case, the matching of the estimated parameters with the actual parameters would be successful. However, the problem is that pairing cannot be instantaneous with the system running. Various studies have proposed a compromise between the precision of the estimation and the speed of the matching by implementing, more sophisticated algorithms, on specialized platforms of embedded controllers [35–37]. For this, in automated systems, different types of observers, state filters and controllers are offered as estimators. The robustness of the controller is supported by the use of adaptive methods. Large-capacity microcontrollers can improve controller board design and software required for estimation, which iteratively targets the match simultaneously.

## 4.2. *Observation–modeling pairing in complex procedures*

Real-time pairings in complex processes are present in different natural circumstances practiced or involved in functions. In addition, online matching of complex procedures is used in many innovative applications.

### 4.2.1. *Modeling matching observation in natural processes*

As mentioned in Section 1, creatures often engage in the practice of sensory observation and simultaneously use deductive skills to manage their natural lives. Also that the activities of deduction and prediction associated with observation are one of the first natural duties born in the world. In this section, we will discuss and analyze two natural processes, the dynamic adaptive camouflage in ecology and the Bayesian Brain theory in neuroscience.

**Dynamic camouflage.** In nature, based on observation, cases of mimetic simulation (imitation strategy) are very frequent allowing camouflage [1]. This permits creatures to blend into their surroundings. It may be a predation strategy or an anti-predation adaptation. It relates to camouflage and imitation that may involve visual, olfactory or auditory cover-up through sensory systems. There are two main categories of camouflage. A form of camouflage consists in the selection of a support, of the environment on which to "land" or/and "disappear". The second form of camouflage is that of dynamic metamorphosis. The first corresponds to choose a matched environment in a single step, and the second corresponds to a self-adapting (transfiguration) dynamic matching. Thus, we have an offline matching resulting from a single observational imitation in the first case and an online dynamic adapting matching in the second. There is a significant literature regarding the multiplicity, processes, roles, and evolution of camouflage, which is measured by the sensory systems of predators targeted by camouflage; see e.g. [38, 39]. This depends on the ability of predators to identify the impacts of predation-enforced selection, where changes in environmental characteristics can be quantified. The victim needs, even if it is complex, to identify changes in the visual systems, cognition and behavior of predators. Just as any victim often uses multiple forms of encryption; it is likely that their predators have multiple ways to defeat them, in response to multiple types of prey. Indeed, the mimetic victim individual adopts the appearance and colors of its environment and remains motionless so as not to be detected by its predators. In addition to color, some organisms are also able to take on the shape of their viewpoint object. Many insects can thus take on the appearance of branches or leaves. This defensive imitation gives the individual protection against predation. There are also cases of offensive imitation, which allows the mimetic individual to chase his victim without being noticed.

The junction between observation capacities and mimetic capacities is practiced in a successive way, which allows the improvement of these capacities.

**Bayesian brain theory.** The Bayesian theory of the brain in neuroscience is widely recognized when it comes to brain function. This theory briefly indicates that after a cerebral sensory observation (vision, smell, hearing, etc.), the predictive model of the brain generates, from the learned data, cerebral perspectives of the observed phenomenon or object. Note that in this case, the predictive model is managed by a sophisticated supercomputer (Human brain: $10^{11}$ neurons each linked to $10^4$ others). Bayesian brain theory explains the cognitive abilities of the brain to work under circumstances of uncertainty to reach the optimum advocated by Bayesian methodologies [40]. It is assumed that neural structure retains inner probabilistic patterns revised by sensory information via neural processing [41]. Bayesian inference works at the level of cortical macrocircuits, which are structured according to a hierarchy that mirrors the observable object scenes around us. The brain encodes a model of these objects and makes predictions about their sensory input: predictive coding. The corresponding areas of brain activity will be near the top hierarchy. The links from the upper zones to the lower zones then convert a model describing the scenes. The lowest-level predictions are compared to the sensory inputs and the prediction error is distributed up the hierarchy. This happens simultaneously at all hierarchical levels. Predictions are sent and prediction errors are returned in a dynamic process. The prediction error indicates that the actual model did not fully account for the input. The next level readjustment can increase the accuracy and reduce the prediction error [42, 43]. It is clear that the observation–prediction duo works in a real-time two-way matching process.

#### 4.2.2. *Matching twins in complex procedures*

In this section, matched twins in complex procedures will be examined, which helps to expose the concept of digital twin. In Section 4.1, we examined the role of the matching of estimated and actual parameters in automated procedures. This illustrated the need to improve the matching of virtual models to their real procedures. We have seen that the nature of a real system and the uncertainty of the emulation process often makes it difficult to build a realistic virtual system and that we need a compromise between estimation accuracy and speed adaptation in automated systems. These two remarks are related to the improvement of the matching of virtual models to their real procedures. Such an action depends on the qualities of the virtual model and its interaction with the real procedure. The quality of the virtual model is associated with its ability to account for the environmental phenomena involved in the actual procedure. The characteristic of the "real–virtual" link is connected to detection, processing and control capabilities. The weight of the matching improvement becomes particularly crucial in compound procedures where the complexity concerns the various incorporated components accounting for the physical phenomena involved (the notion of complexity will be discussed in the next paragraph). To handle such complex procedures, one can practice the Internet of Things (IoT) which intensely deliberates in the physical domain via direct real-time data collection, or Computer Aided Design (CAD), which focuses exclusively on digital territory. However, it is essential to temper and control the irregular and unnecessary behaviors that occur in these complex procedures. Achieving such a goal requires a matched observation–model twin practiced in the relevant procedure [44]. A consistent representation of such a matched twin is shown in Figure 2. Such a twin differs from both IoT and CAD by focusing on both the physical and digital spheres. This twin requires the practice of different skills mainly involving detection (observation side), calculation (model side) and the information and control link (between observation side and model side). Detection on the observation side concerns the various recognitions of the sensors. Model-side computation could involve simulation, optimization, design, diagnosis, prediction,

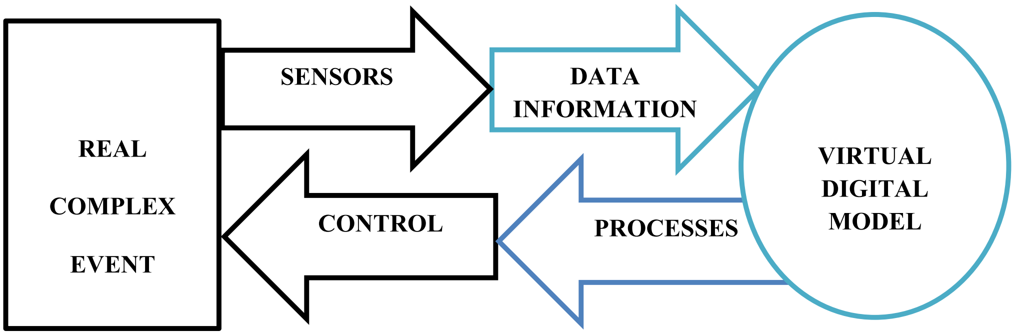


**Figure 2.** Schematics of a real-time bidirectional matched observation–model twin in a complex procedure.

and testing. These operations can use learned collected data in addition to sensor data. The link between the observation side and the model side is bidirectional. The observation part provides sensor measurements in processed form to the model part while the latter sends process and control information to the observation part.

4.2.3. *Complex systems*

Generally, in the so-called complex procedure, the complexity concerns the components and the physical phenomena involved. Complexity can be defined in terms of interactions [45]. These can be classified into three forms: simple, complicated and complex interactions. The former simply behaves in a direct or linear manner, complicated interactions are linear and loosely coupled while complex interactions with tightly coupled links would be characteristic of a complex system or procedure. Such a classification is reminiscent of the one mentioned previously in Section 3.3, relating to the coupling of different phenomena.

Coupling in a complex system involves its various components. This could represent an oversized model and we can use model reduction techniques, see e.g. [46], while preserving accuracy depending on the application concerned (modeling, design, optimization or online supervision).

4.2.4. *Digital twin concept*

The twin described in Section 4.2.2 (Figure 2) corresponds to the Digital Twin DT. Grieves [44] first introduced this concept in 2002. It is distinguished by a beneficial two-way communication between the digital and physical spheres. The three components of a DT are a paired physical observable, a real-time replicated digital element, and their sensory, processing, control, and pairing links. The physical element dynamically adjusts its behavior in real time according to the recommendations made by the digital element. While the digital item correctly reproduces the real state of the territory of the physical product. Thus, DT offers an intelligent alliance of the physical and digital domains. Thus, in DT technology, physical observation and virtual modeling are interconnected in a reciprocal exchange in real time. The observed element corrects the virtual error and the virtual element corrects the observed sensory data. This iterative process leads to a more objective and intelligent association. The DT concept is mainly used for fault diagnosis, predictive maintenance, performance analysis and product design [47]. This concerns various fields and innovative industrial devices such as energy and utilities, aerospace and defense, automotive transport, machinery manufacturing, healthcare and consumer goods.

Note that similar uses of the concept of DT existed [48] before its introduction in 2002 by Grieves [44]. As early as 1993, in “Mirror Worlds”, David Gelernter evoked a similar concept, the possibilities of software models, which represent a portion of reality [49]. However, even before that, NASA used complex simulations to monitor spacecraft safety [50]; then came the unexpected explosion of the oxygen tank of the Apollo 13 mission in 1970 [51]. Following this accident, the mission modified several high-fidelity simulators to adapt them to the real conditions of the damaged spacecraft and used them to land safely [52]. This was probably one of the first real applications of a DT. This involved several basic features of a DT, although it was not a familiar concept in 1970.

4.2.5. *Examples of applications of DT*

Given the huge number of publications on DT, and to illustrate the range of applications, from manufacturing to smart cities, we will provide several examples from different areas of this work. One of DT's most widely used businesses is industrial manufacturing and product design. For example, the pairing of physical and virtual products can be used for the iterative redesign of an existing product or for the creation of a new product. Such DT-based product design can guide manufacturers to support the product design process, see e.g. [53, 54]. Additionally, the integration of manufacturing data and sensory data in the development of DT virtual products that can enhance cyber-physical manufacturing capabilities can be valuable [55]. Another activity of DT concerns predictive maintenance, which is used in many fields. In the context of industrial procedures, predictive maintenance has become an important concern; the main objective is to optimize the maintenance schedule by predicting system and process failures. Such an approach will result in a reduction in unplanned system downtime and severe outages. In addition, the advantages are the minimization of costs and the reduction of the substitution of fundamental elements of the system, see e.g. [56–59]. Additionally, we can mention healthcare services using DT technology as an exciting and encouraging approach that can promote progress efforts in medical innovations and improve clinical and societal health outcomes [60, 61]. In addition, DT's security business as Cyber DT designed for cybersecurity protection [62] and security of DT-based industrial automation and control systems [63]. Also in control, DT technology is used for applications in control centers of electrical systems and in mechatronic systems [64]. Another activity concerns the application of DT technology in EV smart electric vehicles. This concerns various aspects such as autonomous navigation control, driver assistance systems, vehicle health monitoring, battery management systems, electronics and electric drive systems [65, 66]. In addition to the mentioned examples of using DT, we can mention some innovative applications. The application of DT in the livestock sector to improve large-scale precision farming practices, machinery and equipment use, and the health and well-being of a wide variety of animals [48]. Moreover, the application of DT in smart cities to ensure smart aspects in real estate, transportation, construction, health system, building, home, transportation and parking [67].

## 5. Conclusions

The analysis, discussion and evaluation carried out in this contribution have brought to light the following points. Offline matching in the observation–theory link has proven effective in managing and governing elegant theories. We can synthesize the characters of this duo as follows, a mathematical theory simply needs observation to be credible and observation needs a theory to be universal allowing further research. Real-time pairing in the observation–modeling link governs natural phenomena and requires comprehensive models in the supervision of automated and complex physical procedures to behave in the most advantageous manner. The DT concept has shown a wide range of innovative applications with promising capabilities in various modern everyday uses.

## Declaration of interests

The authors do not work for, advise, own shares in, or receive funds from any organization that could benefit from this article, and have declared no affiliations other than their research organizations.

## Funding

This research received no external funding.

## References

[1] H. W. Bates, "Contributions to an Insect Fauna of the Amazon Valley. Lepidoptera: Heliconidae", *Trans. Linnean Soc. Lond.* **23** (1862), no. 3, p. 495-566.
[2] J. C. Maxwell, "A dynamical theory of the electromagnetic field", *Phil. Trans. R. Soc. Lond.* **155** (1865), p. 459-512.
[3] A. Razek, "Coupled models in electromagnetic and energy conversion systems from smart theories paradigm to that of complex events: a review", *Appl. Sci.* **12** (2022), article no. 4675.
[4] A. Razek, "Review of pairing exercises involving a real event and its virtual model up to the supervision of complex procedures", *J. Human Earth Future* **2** (2021), no. 4, p. 424-437.
[5] P. Leitão *et al.*, "Smart agents in industrial cyber-physical systems", *Proc. IEEE* **104** (2016), no. 5, p. 1086-1101.
[6] M. Abramovici *et al.*, "Reconfiguration of smart products during their use phase based on virtual product twins", *CIRP Annals - Manuf. Technol.* **66** (2017), no. 1, p. 165-168.
[7] W. Kritzinger *et al.*, "Digital twin in manufacturing: a categorical literature review and classification", *IFAC-Pap. Online* **51** (2018), no. 11, p. 1016-1022.
[8] D. Jones *et al.*, "Characterising the digital twin: a systematic literature review", *CIRP J. Manuf. Sci. Technol.* **29** (2020), p. 36-52.
[9] C. Lévi-Strauss, *Structural Anthropology*, Basic Books, Paris, 1958.
[10] H. Spiegelberg, "The phenomenological philosophy of Maurice Merleau-Ponty (1908–1961)", in *The Phenomenological Movement*, Springer, Dordrecht, 1971, Second Edition. Mouton de Gruyter, Berlin, New York, 1991, p. 516-562.
[11] E. Schrödinger, "An undulatory theory of the mechanics of atoms and molecules", *Phys. Rev.* **28** (1926), no. 6, p. 1049-1070.
[12] D. J. Wineland *et al.*, "Experimental issues in coherent quantum-state manipulation of trapped atomic ions", *J. Res. Nat. Inst. Standards Technol.* **103** (1998), no. 3, p. 259-338.
[13] M. Brune, S. Haroche *et al.*, "Manipulation of photons in a cavity by dispersive atom–field coupling: quantum-nondemolition measurements and generation of Schrödinger cat states", *Phys. Rev. A* **45** (1992), no. 7, p. 5193-5214.
[14] J. C. Maxwell, *A Treatise on Electricity & Magnetism*, Dover Publications, New York, 1873, ISBN 0-486-60636-8 (Vol. 1) & 0-486-60637-6 (Vol. 2): https://www.aproged.pt/biblioteca/MaxwellI.pdf.
[15] E. H. Hall, "On a new action of the magnet on electric currents", *Amer. J. Math.* **2** (1879), no. 3, p. 287-292.
[16] A. Laesecke, "Through measurement to knowledge: the inaugural lecture of Heike Kamerlingh Onnes (1882)", *J. Res. Nat. Inst. Standards Technol.* **107** (2002), no. 3, p. 261-277.
[17] S. Haykin, "Neural networks: a guided tour", in *Soft Computing and Intelligent Systems*, Academic Press, San Diego, 2000, Chapter 3, p. 71-80.
[18] G. W. Burr *et al.*, "Neuromorphic computing using non-volatile memory", *Adv. Phys.: X* **2** (2016), no. 1, p. 89-124.
[19] R. P. Feynman, "Simulating physics with computers", *Int. J. Theoret. Phys.* **21** (1982), no. 6–7, p. 467-488.
[20] D. Castelvecchi, "Quantum computers ready to leap out of the lab in 2017", *Nature* **541** (2017), no. 7635, p. 9-10.
[21] A. K. Fedorov, E. O. Kiktenko, A. I. Lvovsky, "Quantum computers put blockchain security at risk", *Nature* **563** (2018), no. 7732, p. 465-467.
[22] Z. Ren, A. Razek, "New technique for solving three-dimensional multiply connected eddy-current problems", *IEE Proc. A: Phys. Soc. Meas. Instr.* **137** (1990), no. 3, p. 135-140.
[23] C. Li, Z. Ren, A. Razek, "An approach to adaptive mesh refinement for three-dimensional eddy-current computations", *IEEE Trans. Magn.* **30** (1994), no. 1, p. 113-117.
[24] F. Piriou, A. Razek, "A non-linear coupled 3D model for magnetic field and electric circuit equations", *IEEE Trans. Magn.* **28** (1992), no. 2, p. 1295-1298.
[25] F. Piriou, A. Razek, "Numerical simulation of a nonconventional alternator connected to a rectifier", *IEEE Trans. Energy Conv.* **5** (1990), no. 3, p. 512-518.
[26] E. Mendes *et al.*, "Losses minimization of a field oriented controlled induction machine", in *Seventh International Conference on Electrical Machines and Drives (IET)*, IET, Durham, 1995, p. 310-314.

[27] Z. Ren, A. Razek, "A strong-coupled model for analyzing dynamic behaviors of non-linear electromechanical systems", *IEEE Trans. Magn.* **30** (1994), no. 5, p. 3252-3255.
[28] F. Bay *et al.*, "A numerical model for induction heating processes coupling electromagnetism and thermomechanics", *Int. J. Numer. Meth. Eng.* **58** (2003), p. 839-867.
[29] C. Jörgens, M. Clemens, "Electric field and temperature simulations of high-voltage direct current cables considering the soil environment", *Energies* **14** (2021), article no. 4910.
[30] A. Sekkak, L. Pichon, A. Razek, "3-D FEM magneto-thermal analysis in microwave ovens", *IEEE Trans. Magn.* **30** (1994), no. 5, p. 3347-3350.
[31] H. Hariri *et al.*, "Dual piezoelectric beam robot: the effect of piezoelectric patches' positions", *J. Intel. Mat. Syst. Struct.* **26** (2015), no. 18, p. 2577-2590.
[32] S. A. Rios, A. J. Fleming, Y. K. Yong, "Miniature resonant ambulatory robot", *IEEE Robot. Autom. Lett.* **2** (2017), no. 1, p. 337-343.
[33] M. Besbes, Z. Ren, A. Razek, "A generalized finite element model of magnetostriction phenomena", *IEEE Trans. Magn.* **37** (2001), no. 5, p. 3324-3328.
[34] O. Bottauscio, P. E. Roccato, M. Zucca, "Modeling the dynamic behavior of magnetostrictive actuators", *IEEE Trans. Magn.* **46** (2010), no. 8, p. 3022-3028.
[35] G. Soto *et al.*, "Reduced-order observers for rotor flux, rotor resistance and speed estimation for vector control induction motor drives using the extended Kalman filter technique", *IEE Proc.-Elec. P. App.* **146** (1999), no. 3, p. 282-288.
[36] F. Alonge *et al.*, "Sensorless control of induction-motor drive based on robust Kalman filter and adaptive speed estimation", *IEEE Trans. Indust. Electron.* **61** (2014), no. 3, p. 1444-1453.
[37] C. El Moucary, E. Mendes, A. Razek, "Decoupled direct control for PWM inverter-fed induction motor drives", *IEEE Trans. Indust. Appl.* **38** (2002), p. 1307-1315.
[38] J. Galloway *et al.*, "Finding a signal hidden among noise: how can predators overcome camouflage strategies?", *Phil. Trans. R. Soc.* **375** (2020), no. 1802, article no. 20190478.
[39] N. Price *et al.*, "Background matching and disruptive coloration as habitat-specific strategies for camouflage", *Sci. Rep.* **9** (2019), article no. 7840.
[40] D. C. Knill, A. Pouget, "The Bayesian brain: the role of uncertainty in neural coding and computation", *Trends Neurosci.* **27** (2004), no. 12, p. 712-719.
[41] W. Penny, "Bayesian models of brain and behaviour", *ISRN Biomath.* **2012** (2012), p. 1-19.
[42] A. Pouget *et al.*, "Probabilistic brains: knowns and unknowns", *Nat. Neurosci.* **16** (2013), no. 9, p. 1170-1178.
[43] J. Hohwy, "Priors in perception: top-down modulation, Bayesian perceptual learning rate, and prediction error minimization", *Conscious. Cogn.* **47** (2017), p. 75-85.
[44] M. Grieves, J. Vickers, "Digital twin: mitigating unpredictable, undesirable emergent behavior in complex systems", in *Transd Perspe on Complex Systems*, Springer, Cham, 2017, p. 85-113.
[45] C. Perrow, *Normal Accidents: Living with High Risk Technologies - Updated Edition*, Princeton University Press, Princeton, NJ, 2011.
[46] B. Besselink *et al.*, "A comparison of model reduction techniques from structural dynamics, numerical mathematics and systems and control", *J. Sound Vibr.* **332** (2013), no. 19, p. 4403-4422.
[47] B. He, K. J. Bai, "Digital twin-based sustainable intelligent manufacturing: a review", *Adv. Manuf.* **9** (2021), no. 1, p. 1-21.
[48] S. Neethirajan, B. Kemp, "Digital twins in livestock farming", *Animals* **11** (2021), no. 4, article no. 1008.
[49] D. Gelernter, *Mirror Worlds: Or the Day Software Puts the Universe in a Shoebox … How It Will Happen and What It Will Mean*, Oxford University Press, Oxford, 1993.
[50] F. Tao *et al.*, "Make more digital twins", *Nature* **573** (2019), no. 7775, p. 490-491.
[51] G. A. Boy, *Human–Systems Integration: From Virtual to Tangible*, CRC Press, Florida, 2020.
[52] C. Zhuang *et al.*, "The connotation of digital twin, and the construction and application method of shop-floor digital twin", *Robot. Comput.-Integr. Manuf.* **68** (2021), p. 1-16.
[53] F. Tao *et al.*, "Digital twin-driven product design framework", *Int. J. Product. Res.* **57** (2019), no. 12, p. 3935-3953.
[54] B. He, K. J. Bai, "Digital twin-based sustainable intelligent manufacturing: a review", *Adv. Manuf.* **9** (2021), no. 1, p. 1-21.
[55] Y. Cai *et al.*, "Sensor data and information fusion to construct digital-twins virtual machine tools for cyber-physical manufacturing", *Proc. Manuf.* **10** (2017), p. 1031-1042.
[56] Ş. Y. Selçuk *et al.*, "A workflow for synthetic data generation and predictive maintenance for vibration data", *Information (Switzerland)* **12** (2021), no. 10, article no. 386.
[57] J. J. Montero Jimenez *et al.*, "Towards multi-model approaches to predictive maintenance: a systematic literature survey on diagnostics and prognostics", *J. Manuf. Syst.* **56** (2020), p. 539-557.
[58] M. Nacchia *et al.*, "A systematic mapping of the advancing use of machine learning techniques for predictive maintenance in the manufacturing sector", *Appl. Sci. (Switzerland)* **11** (2021), no. 6, article no. 2546.

[59] Z. Liu, N. Meyendorf, N. Mrad, "The role of data fusion in predictive maintenance using digital twin", *AIP Conf. Proc.* **1949** (2018), article no. 020023.

[60] Y. Liu *et al.*, "A novel cloud-based framework for the elderly healthcare services using digital twin", *IEEE Access* **7** (2019), p. 49088-49101.

[61] M. N. Kamel Boulos, P. Zhang, "Digital twins: from personalised medicine to precision public health", *J. Person. Med.* **11** (2021), no. 8, article no. 745.

[62] D. Holmes *et al.*, "Digital twins and cyber security – solution or challenge?", in *Computer Engineering, Computer Networks and Social Media Conference (SEEDA-CECNSM, 1–8)*, 2021.

[63] C. Gehrmann, M. Gunnarsson, "A digital twin based industrial automation and control system security architecture", *IEEE Trans. Indust. Inform.* **16** (2020), no. 1, p. 669-680.

[64] S. Boschert, R. Rosen, *Digital Twin-The Simulation Aspect. Mechatronic Futures: Challenges and Solutions for Mechatronic Systems and Their Designers*, Springer, Switzerland, 2016.

[65] G. Bhatti, H. Mohan, R. Raja Singh, "Towards the future of smart electric vehicles: digital twin technology", *Renew. Sustain. Energy Rev.* **141** (2021), article no. 110801.

[66] X. Chen *et al.*, "Dynamic safety measurement-control technology for intelligent connected vehicles based on digital twin system", *Vibroeng. Proc.* **37** (2021), p. 78-85.

[67] S. Shirowzhan *et al.*, "Digital twin and CyberGIS for improving connectivity and measuring the impact of infrastructure construction planning in smart cities", *ISPRS Int. J. Geo-Inf.* **9** (2020), no. 4, article no. 240.