Chapter 3
Simulation-Based Engineering

Melih Cakmakci, Gullu Kiziltas Sendur and Umut Durak

Abstract Engineers, mathematicians, and scientists were always interested in numerical solutions of real-world problems. The ultimate objective within nearly all engineering projects is to reach a functional design without violating any of the performance, cost, time, and safety constraints while optimizing the design with respect to one of these metrics. A good mathematical model is at the heart of each powerful engineering simulation being a key component in the design process. In this chapter, we review role of simulation in the engineering process, the historical developments of different approaches, in particular simulation of machinery and continuum problems which refers basically to the numerical solution of a set of differential equations with different initial/boundary conditions. Then, an overview of well-known methods to conduct continuum based simulations within solid mechanics, fluid mechanics and electromagnetic is given. These methods include FEM, FDM, FVM, BEM, and meshless methods. Also, a summary of multi-scale and multi-physics-based approaches are given with various examples. With constantly increasing demands of the modern age challenging the engineering development process, the future of simulations in the field hold great promise possibly with the inclusion of topics from other emerging fields. As technology matures and the quest for multi-functional systems with much higher performance increases, the complexity of problems that demand numerical methods also increases. As a result, large-scale effective computing continues to evolve allowing for efficient and practical performance evaluation and novel designs, hence the enhancement of our thorough understanding of the physics within highly complex systems.

M. Cakmakci (✉)
Department of Mechanical Engineering, Bilkent University, Ankara, Turkey
e-mail: melihc@bilkent.edu.tr

G. Kiziltas Sendur
Mechatronics Engineering Program, Faculty of Engineering and Natural Sciences,
Sabanci University, Istanbul, Turkey
e-mail: gkiziltas@sabanciuniv.edu

U. Durak
Institute of Flight Systems, German Aerospace Center (DLR), Braunschweig, Germany
e-mail: umut.durak@dlr.de

3.1 Introduction

3.1.1 Overview of the Engineering Design Process

The ultimate objective of all engineering projects is to reach a functional design without violating any of the performance, cost, time, and safety constraints often optimizing the design for one of them. Generally, in the beginning of each project high-level requirements for the system is developed. These high-level requirements can be as literal as "*The fuel consumption of the vehicle shall be* 40 mpg *or more.*" or comparative such as "*The new CNC machine will be as precise as our competitors.*" Then, these high-level requirements are cascaded down to the lower levels of the system design steps to obtain the well-defined engineering design problems.

Engineering design problems are concrete problem constructs that contain quantifiable performance and constraint metrics. The inputs to the engineering problems are the performance constraints, design parameters, external conditions. The output of the engineering design process is the design communicated in technical terms such as materials, dimensions, and algorithms. Usually, a lesser focused output of an engineering project is the operation recommendations, lifecycle maintenance, and storage instructions. In general, main steps of the engineering design process can be given as, requirements analysis, design, implementation, verification, and maintenance.

In Fig. 3.1, inputs and outputs of the engineering development process is given as discussed previously. It is also important to note that this process can be applied at the component, the sub-system (i.e., group of interrelated components), and at the system level.

Over time, two primary approaches emerged to approach the solution of complex engineering design projects.

The early approach also known as the "Waterfall Design Process", the sub-problems can be tackled and solved sequentially. Even though, it provides a structured method to perform design and testing tasks, its sequential nature fails to catch design-related errors early in the development process.

Inspired from the approaches in development of software intensive systems, as an extension of "Waterfall Design Process", a new engineering design approach has emerged which is called the "V-process" where relations of design and validations
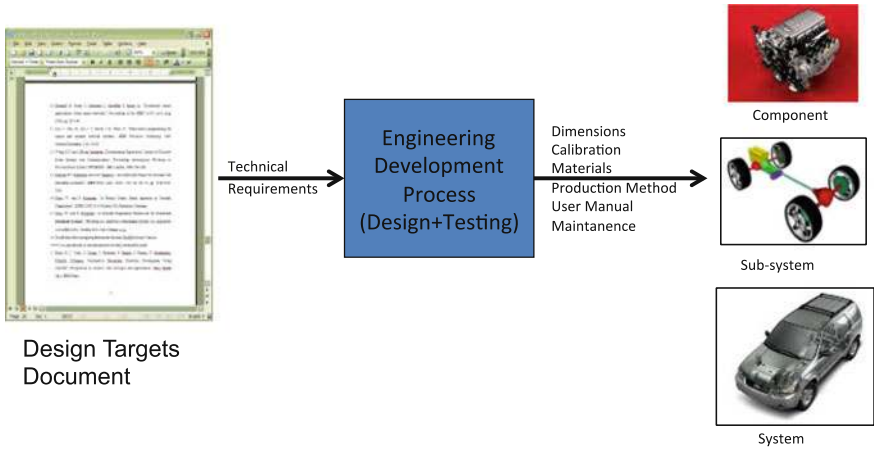
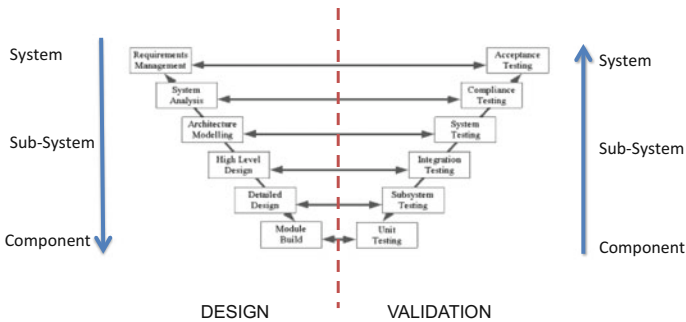**Fig. 3.1** Engineering development process

Fig. 3.2 Engineering V-process

steps are stressed. Simulations of varying resolution and fidelity become important tool in the V-process, in order to conduct validations as well as the evaluations of design decisions before the actual prototype of the system can be build.

In Fig. 3.2, the typical steps of the V-process is given based on (Ulsoy et al. 2012). The essence of the V-process is to cascade from the system level to the smaller scale such as the component level and the level-based validation of the work to catch problems at early stages. The different levels of validation and design work in the V-process increase the importance of effective simulations throughout the whole process.

Today almost all of the engineering community is using the iteration based V-diagram process. One of the early hesitation points regarding the engineering V-process was also its strongest feature, namely the existence of stepwise iterations and the cost they bring to the overall development. However, the evolution of

advanced simulation techniques made iterations more manageable minimizing the cost of rework during development.

One of the most important topics in the simulation development process is the decision of the feature content and their fidelity. Too much content or dynamics and the simulation will be consuming too much computational resources generally resulting in time and cost problems. Too little detail in simulations will result in misguided simulations, missing important modes of the target systems and taking away the benefit of simulation-based iteration in the development process.

When the engineering V-process is considered, the level of validation increases as the project progresses in time as shown in Fig. 3.2. The decomposition of the requirements and development process requires a proof-of-concept simulation first, which are detailed in physics but abstract at the interface level. When the test phase starts these component-based simulations are combined to produce sub-system and system-level simulations that are also advanced in terms of the mechanical and electronics interactions (the interface) of the system. The sub-system and system-level simulations are more detailed than the component-level simulations.

In most engineering development projects, the understanding of the target system improves with the progress of the project. Therefore, the resolution and fidelity of the simulations can also be improved using the new data and understanding of system of interest.

Generally, in the early stages of the engineering development process a prototype of the target system does not exist. However, a concept emulating simulation of the system can be developed using existing models from the company's resources or from the existing technical literature. When these simulations are functional, the new feature of the system can be included in the model and the simulations can be used to make early predictions about the performance of the target system with fairly good confidence. These simulations can be used to verify the feature-based requirements in the V-process. These simulations are usually known as feature-in-the-loop simulations.

Figure 3.3 shows a simulation case where a new feature (Feature A) in the system is simulated with the already validated features (Features B-E). Even though the system (Features A-E) may have more than one component, in feature-in-the loop simulations the physical boundaries and interfaces are not considered.

After enough confidence is gained about the feature-in-the-loop simulations for the new features of the components, component-in-the-loop simulations can be developed. Component-in-the-loop simulations usually contain all the newly developed features of the system. Feature-in-the-loop simulations are generally done separately for easy troubleshooting and for de-coupling of individual contributions.

Component-in-the-loop simulations contain all the new and carry-over features as well as the actual electronic and mechanical interface of the system. These simulations are used in the component-level testing for the engineering development process. When prepared properly with the actual system-level interface they can be directly used in system simulations that include all components of the system both electric and mechanical.

Fig. 3.3 Feature-in-the-loop simulations
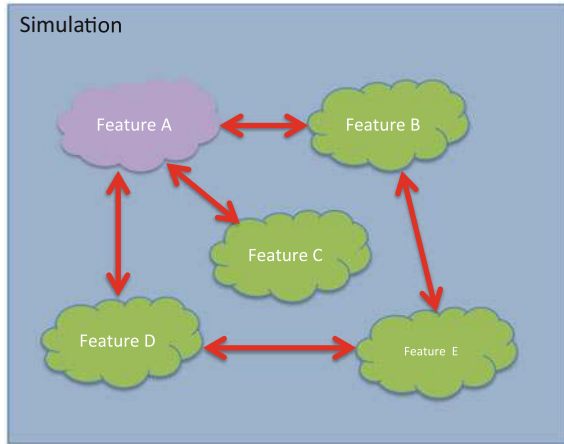
Fig. 3.4 Component-in-the-loop simulations
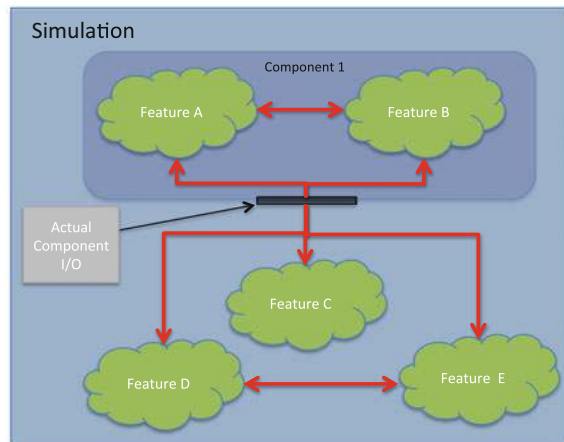
In Fig. 3.4, a component-in-the-loop simulation scenario is given. The work is done all in the simulation environment, however, a notion of the component physical boundaries exists that forces the interaction of Features A and B through a common interface as compared to the feature-in-the-loop simulation given in Fig. 3.3. Generally, this interface is developed as the proposed physical and electrical interface of the component with the rest of the system.

One of the most important challenges of an engineering development process is to work in a task-based team environment, where different teams are in charge of different features/components/sub-systems of the project. The development cycle of different targets can be at different stages at different times, which makes it difficult to validate functionality with the complete configuration of the system. Testing with hardware-in-the-loop simulations is an approach developed by engineers to overcome this problem. In hardware-in-the loop simulations part of the system is

emulated using computers using simulations and part of the system is the actual hardware, which already designed or carried over from the previous version of the system. In many cases the benefit of the HIL simulations are bidirectional in the sense that they can both be used for improving the quality of the simulations using it against the actual hardware or testing a specific prototype hardware for functionality while emulating the rest of the system.

Figure 3.5 shows a hardware-in-the-loop scenario for the system and features given in Figs. 3.3 and 3.4. This time the actual hardware of the component that includes Features A and B are run against the rest of the system (Features C–E) all simulated in the computer environment. It is also important to note that the preparation of the simulations in the earlier stages help to build successive versions of the feature, component and hardware-in-the-loop simulations. For example the physical and electrical based build of the interface in the component level increase the reuse of the component representation in the hardware-in-the-loop simulations.

A good example of the simulation-based V-process development is the so-called mode-based controller development process (MBCD) in the automotive industry. In (Ulsoy et al. 2012), a technical requirements development method is shown for a specific battery control module example. This example shows how the vehicle 100,000-mile requirement affects specific features (control problems) for a particular vehicle application. The effect of this requirement and others define the feature control problem to be solved. The solutions obtained from all of the features represent the control algorithm for a vehicle.

In the design step, first the control design problem is formulated based on the given performance requirements and developed mathematical formulation. There will be more than one control design approach, which will provide a solution for the control problem. By using analytical methods and/or computer simulations, the best alternative among these candidate algorithms is selected. If the control problem is similar to an earlier application, development teams often prefer to start with an


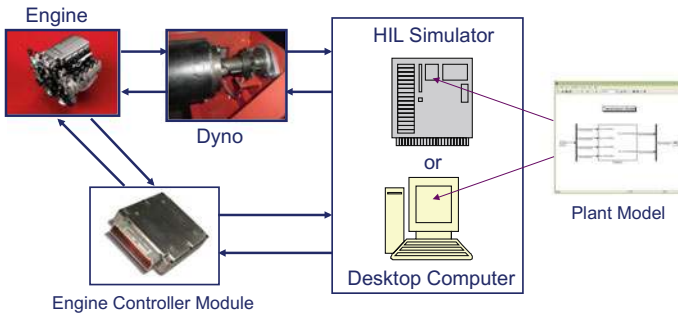**Fig. 3.5** Hardware-in-the-loop simulations
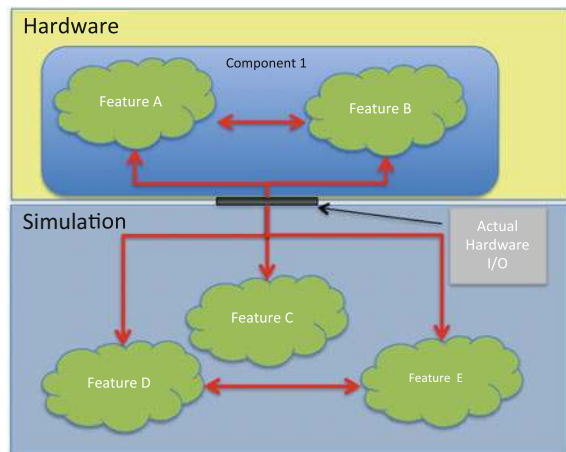
existing control algorithm and try improve the solution by building upon the existing (and proven) solution.

Then the design is implemented on the actual hardware. During the implementation phase the objective is to develop a real-time application, which will be executed in the control module using the desired control algorithm. While developing the executable code the real-time constraints of the target hardware (i.e., the controller module) should also be considered. Software implementation of the algorithm should be matched to the computing resources available and if there are overruns during the real-time execution simplifications in the algorithm should be made, or new target hardware should be selected. In today's modern vehicles, controller modules also communicate with other controllers via communication networks. The effects of the loss of this communication with one or more contacts or the cases of limited communications should be investigated and necessary modifications should be made.

Testing in the MBCD process starts as early as in the algorithm development step. By testing the algorithms open-loop (Fig. 3.6a) developers can feed in simple test vectors and analyze the test output for expected functionality. These simple algorithms can also be tested against the simpler conceptual vehicle models, which are available in the earlier stages of the program (Fig. 3.6b). These models are later

(a) Open Loop Testing

(b) Algorithm-in-the-Loop Testing

(c) Controller Model-in-the-Loop Testing
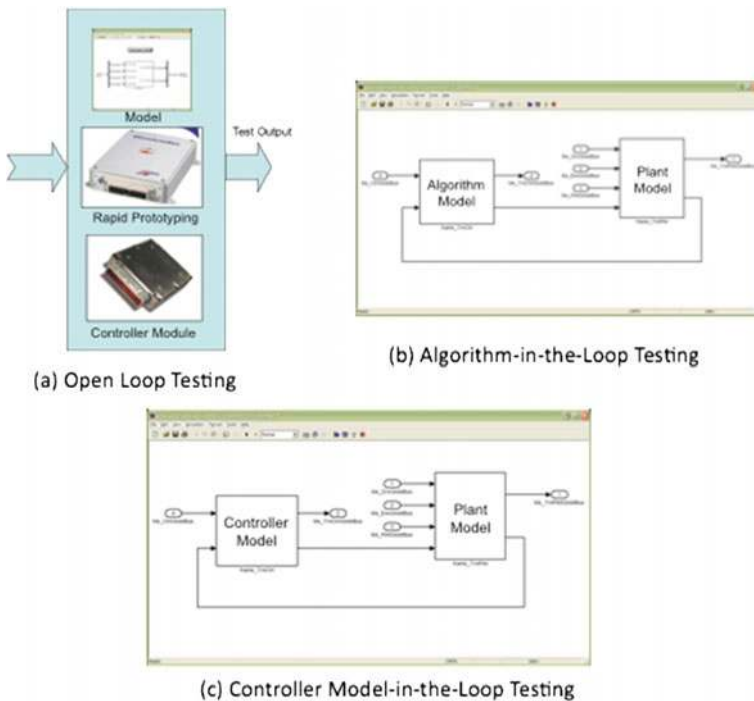
Fig. 3.6 Different types of testing in automotive industry

Fig. 3.7   Different types of testing in automotive industry (cont'd)

fortified with improvements based on component and vehicle testing data, which makes them suitable for more complex testing procedures such as module, component and vehicle in the loop types of testing.

In the later stages of the vehicle development process, a hardware-in-the-loop simulation can be run to see the proper operation of the vehicle controller using part real hardware and part simulations run in the computer environment as shown in Fig. 3.7.

3.1.2   Source of Models

Models are purposeful abstractions of the real world. With abstraction while certain aspects of the system are explicitly represented, other aspects are omitted that are not of concern (Topçu et al. 2016). They can be physical, mathematical, and/or logical (Sokolowski and Banks 2010). The scaled aircrafts that are used in wind tunnels are very good examples of physical models. When they are not physical, models are composed of a series of mathematical equations and/or logical expressions. These models can be physics-based, data-based, or hybrid (combined).

Physics-based models can be defined as the ones which are essentially mathematical and the governing equations are based on physical principles such as thermodynamics laws or Newton's law of motion.

The application of physics-based models in engineering domain is so common. Since early the days of engineering, Newton's law of motion has been used for modeling rigid bodies. Dynamics of machinery is an engineering field that deals with forces and moments and their effects on the motion. The theory of machines studies the relative motion of machine elements under the effects of external forces (Khurmi and Gupta 1976).

Modeling the mechanical behavior as a continuous mass is the topic of continuum mechanics. It is concerned with the stress in the continuous medium (solids, liquids or gases) and their deformation or flow (Malvern 1969). Continuous as an adjective is used to express the approximation that assumes the mass without gaps

and empty spaces thereby representing the mathematical functions as well as their derivatives are continuous. This hypothetical medium is called continuum. The governing physical laws in this case are conservation of mass, momentum, and energy. These equations will be summarized in Sect. 3.2.6. The motion of viscous fluids is mostly computed by applying Navier–Stokes equations which encompasses time-dependent equations for conservation of mass, momentum, and energy. Euler equations are well-employed simplification of Navier–Stokes equations which neglects the effects of viscosity (Schetz and Fuhs 2013). Computational Fluid Dynamics (CFD) is the area of study which applies numerical methods like finite difference or finite volume to solve the approximations of these equations. Physical model of heat has also been built considering it as a fluid inside the matter. Heat equation is a partial differential equation that concerns the distribution of heat in material over time (Widder 1976). Solid mechanics deals with the behavior of solid materials under load. While elasticity is the study of body that retains its original state after releasing the load, plasticity governs the nonreversible deformation of solid. Euler–Bernoulli beam equation and plate theory are well-applied simplifications in modeling and simulation of elastic behavior. They both define the relations between the applied forces and the resulting deflections (Fung 1965). Finite Element Method (FEM) as will be discussed later in Sect. 3.2.3., is commonly employed for approximating partial differential equations within Navier–Stokes equations, heat equation and Euler–Bernoulli beam equation (Dhatt et al. 2012). It promotes using simple approximation of unknown variables to transform partial differential equating to algebraic equations.

Data-based models utilize the data that describes the particular aspects of the system that is subject to modeling. It is also named as empirical modeling since the model depends on empirical observations rather than mathematical equations (Sokolowski and Banks 2010). While the computing power as well as the optimized implementations of finite element analysis and computational fluid dynamics software getting better, engineering design optimization of complex systems like aircrafts or cars requires long lasting simulations which are sometimes unacceptable in practice (Wang and Shan 2007). Additionally, sometimes it is required to incorporate data from the real world into the simulation. Data-based models, or simply called metamodels approximate computation-intensive functions or real-world data to analytical models. The modeling process starts with data collection using sampling methods such as fractional refactoring, or Latin hypercube. Then the model is constructed is a particular method of choice. Polynomial equations, splines, Multivariate Adaptive Regression Splines (MARS), artificial neural networks are some of these methods. Model fitting is done with an appropriate approach like least squares or backpropagation.

Hybrid modeling combines previously mentioned two modeling paradigms. While a part of a physical process is approximated using data models, the rest of the physical process is modeled using equations that represent the law of physics. In modeling and simulation of air vehicles, it is a common practice to develop data models for the aerodynamics modeling, where the flight dynamics is modeled using Newton's laws of motion (Jategaonkar et al. 2004). The aerodynamics data may be

collected from the flight experiments, wind tunnel tests or with CFD runs. Nowadays, the design of complex multidisciplinary systems such as aircrafts, automobiles and similar is carried out using hybrid models within a Multi-Disciplinary Design Optimization (MDO) framework (Martins and Lambe 2013). Such procedures allow designers to incorporate all relevant disciplines simultaneously. The optimum of the coupled problem is superior to the design found by optimally designing each module sequentially, since it can exploit the synergistic coupling between them. However, this concurrent consideration results in a much more complex problem. Therefore, systematic structuring, modeling, and approximation tools have to be employed within MDO, which has been applied with successfully to the design of many commercial products.

3.2 Simulation of Continuum

The term modeling refers to the development of a mathematical representation of a physical situation whereas simulation refers to the procedure of solving the equations that resulted from model development (Ashby 1996). With the development of mathematical models it was possible for scientists to integrate research into natural phenomena within their investigations. Analysis of these models was only possible via existing analytical or numerical methods which by then were only tackled for specific problems. Each of these methods in literature is known by the great scientist who developed them such as Euler, Newton, and Gauss.

Despite major contributions by various outstanding scientists, the main issues concerning the theoretical and physical understanding of the equations in continuum mechanics are still being worked on. Continuum mechanics has changed dramatically since the late nineteenth century, so that theoretical studies are now coined with numerical experimentation and simulation. Furthermore, progress in the computational speed and power allowed researchers to develop mathematical models for much more complex physical problems some of which will be discussed in the multi-scale and multi-physics sections. After the invention of calculus, many advanced PDE's were introduced to describe the physics of systems from different disciplines such as solid mechanics, fluid mechanics, and elastodynamics. Important contributions were initially made by Euler, Lagrange, and Cauchy and these were followed by the application of PDE's to describe the physics of electromagnetic (EM) theory by Maxwell, Heaviside, and Hertz, and finally to quantum mechanics with major theoretical work by Schrodinger. These equations are descriptive of the time evolution and relationship of various fields in a three dimensional space. Major efforts of continuum simulation in the areas of Solid Mechanics, Fluid Mechanics, and Electromagnetics will be described in the next sections to follow.

The introduction of efficient and powerful platforms enabled researchers to solve the constitutive laws of continuum in mechanics in combination with the laws of conservation of mass, energy, and momentum. The same is valid for other fields

including EM. Some of the most popular methods used for this purpose are the Finite Element Method (FEM), Finite Volume Methods (FVM), Finite Difference Methods (FDM), and Boundary Element Methods (BEM). These methods are applied to the simulation of matter in all forms, i.e., solids, liquid, and gas, based on a major assumption of continuum media, thus Computational Mechanics of Continua. Namely, the term continuum describes the nonseparability of the considered domain and validity of continuity between any points in the domain so that differentiation is possible. Therefore, continuity between elements in any continuum-based numerical technique is maintained as well. Unlike analytical exact solutions of differential equations, which allow the solution at every point, the numerical solution is only calculated at chosen finite number of nodes, yielding in turn a reduction in complexity of the system. Well-known methods to conduct continuum-based simulation are described in the next section.

3.2.1 Finite-Difference Method

One of the earliest and widely used numerical method for solving PDE's within continuum mechanics is the Finite-Difference Method (FDM). The main idea of FDM is based on replacing the differential terms with respective to the spatial coordinates with the so-called finite differences over small enough distances based on the Taylor's series approximation. For that purpose, the domain of interest needs first to be discretizedinto vertical and horizontally located nodes, on which finite differences are defined. Several finite difference integration schemes exist known as forward, backward, and central difference schemes. It is worth noting that the FDM is equally applicable to time differentiations. As a result of discretizing the domain into nodes, a system of algebraic equations in terms unknowns at the chosen nodes are constructed. Each algebraic equation belonging to its corresponding node is expressed as a combination of function values at its own node and its neighboring nodes. Next step is to impose boundary conditions, which leads to the solution step of the equation system using either direct or iterative solution methods. Finally, unknowns at each node are solved. This solution is only an approximate solution since the finite differences are first-order approximations of the partial derivatives. The FDM when compared with the FEM or BEM allows for a direct discretization of the equations and does not rely on the use of interpolation functions. Therefore, it is one of the most direct and intuitive techniques that exist for the solution of PDEs. Moreover, for material nonlinearities, the FDM proves to be favorable as it allows their simulation without the need of iterative techniques. However, it suffers from relying on regular noded discretization scheme which makes modeling of irregular geometries a challenging task. This also results in difficulties when heterogeneous material compositions and unusual boundary conditions are present. However, the FDM has been generalized to overcome related shortcomings through methods based on irregular node/grid structures with methods such as irregular quadrilateral, triangular, and Voronoi grids.

3.2.2 Finite Volume Method

The Finite Volume Method is similar to the FDM method and evolved as its successor to solve PDE's with one major difference: these differential equations are expressed in integral form. Its formulation leads to the concept of finite volumes, which essentially correspond to volumes around and encompassing each node in a mesh. Similar to the FDM, algebraic equations of unknowns at nodes are built by replacing the integrals and by considering boundary and initial conditions. Thereby, the system of equations to be solved is constructed. The FVM, similar to the FDM has certain advantages such as allowing the usage of irregular unstructured mesh and modeling capabilities of nonhomogeneous material compositions.

3.2.3 Finite Element Method

The Finite Element Method (FEM) was introduced in the 1960s as an alternative method to FDM for the numerical solution of stress concentration. More importantly, it is the first numerical solution method which was capable of dealing with complexities such as nonlinearities, nonhomogeneous materials, complex geometries, and sophisticated boundary conditions. As a result, FEM was soon recognized as the most popular numerical method in continuum mechanics, mainly so because unlike FDM, it allowed for nonuniform discretization. The method was found more extensive and used a decade later with the theoretical developments made by Bathe (2006) and Zienkiewicz and Taylor (2005). Many researchers have contributed to the development of the method which is by far the most favorite method for the approximate solution of many sophisticated continuum mechanics problems of dynamic, anisotropic, and inelastic behavior. It is a generic numerical solution technique for boundary value problems coming from various disciplines. The main principle rests on the idea of dividing the problem domain into smaller subregions (areas or volumes) called finite elements. This is followed by typical steps of defining local element approximations, performing assembly of finite elements and ultimately solving the resulting global matrix equation. More specifically, the unknown function (e.g., displacement field, temperature field, electric field, velocity and pressure fields) is approximated via trial/interpolation functions of the nodal values (or edge unknowns in EM problems) using polynomial functions. Numerical integration is performed in each element using Gauss quadrature points. After assembly, the algebraic global system of equations is obtained. Because of continuum assumptions, standard FEM methods cannot be directly and efficiently applied to discontinuum problems involving cracks, damage-induced discontinuities or singularities and failure analysis.

In addition to the well-known superiority of the FEM which is well suited for complex analysis of systems composed of heterogeneous materials and irregular geometries owing to the possibility of using an irregular mesh, it also proved to be

an appropriate tool for modeling various nonlinear geometries and inelastic material behavior and nowadays material hardening and softening. Moreover, it has the capability of representing geometric nonlinearities, contact mechanisms, fluid-structure interaction, multi-scales, etc., as will be discussed in separate sections below. Therefore, the FEM will stand out as the mostly used and diverse numerical method in continuum mechanics.

3.2.4   Meshless Methods

The bottleneck in applying FEM to complex engineering problems with intricate geometries, unusual material properties, and complex boundary conditions is the mesh generation process, which usually in 3D problems is an extremely challenging task mostly comparable to the problem solution itself. Another disadvantage of FEM relates to numerical instability due to a distorted mesh. Both of these problems can be avoided by another class of methods known as 'meshless methods', which as the name implies does not rely on elements but interpolation functions are generated from neighboring nodes within a domain of influence. More specifically, nodes are created across the domain without the need of a fixed element topology definition. As a result, the interpolation functions obtained are no longer polynomial functions leading to more difficult numerical integration when compared with the FEM where Gauss integration points are used. Moreover, meshless methods suffer from increased computational requirements but do not rely on standard mesh generators and are able to easily represent more complicated geometries. In literature, methods such as smoothed particle hydrodynamics, diffuse element method (DEM), element-free Galerkin method, reproducing kernel particle methods, moving least squares reproducing kernel method, hp-cloud method, the method of finite spheres, and finite point method stand out.

3.2.5   Multi-scale Methods

All products whether man-made or natural are composed of multiple scales. Taking an example from the aeronautical industry, the Airbus A380 consists of many thousands of structural components and many more sub-structural details. Similarly, its fuselage consists of 750,000 holes and cutouts with different structural and material scales. When viewed at the roughest material scale, fuselage composites' part consists of woven/textile composite and laminate scales; at the intermediate scale, it is composed of a tow or yarn, which consists of a bundle of fibers. When looked at a more discrete scale, including atomistic and ab initio scales, the aircraft's metal part consists of a polycrystalline scale, a single crystal scale, a discrete dislocation scale, and also time atomistic and ab initio scales.

Computations and simulations in the aforementioned multi-scales have been identified as areas of utmost importance to advance the future in nanotechnology. One of the obvious fundamental challenges associated with such a multi-scale approach relates to the increased uncertainty and complexity introduced by these finer scales. However, the application of any multi-scale approach has to be carefully evaluated. For instance, considering metal matrix composites with fibers arranged in a periodic fashion, finer scales could prove useful because the bulk material typically does not obey normality rules, and the development of a phenomenological coarse-scale constitutive model would be extremely difficult. This would also allow a better understanding of each phase and the overall material response could be extracted from its fine-scale constituents via homogenization techniques. However, for brittle ceramic matrix composites, with microcracks that exist in a random distribution and complex interface properties, are difficult to characterize, a multi-scale approach would not be an appropriate alternative.

There are two main categories of multi-scale approaches in literature, namely, hierarchical or concurrent. In the former approach, the fine-scale response is idealized/approximated and its overall/average response is integrated into the coarse scale. In the latter approach, fine and coarse-scale resolutions are simultaneously employed in different portions of the same problem domain, and the exchange of information occurs through the interface. The sub-domains which present themselves at different scale resolutions can be either overlapping or disjoint.

Various hierarchical multi-scale methods have been labeled by different names, including upscaling, coarse-graining, homogenization, or simply multi-scale methods. There are also subcategories of the above definitions, such as systematic upscaling, operator upscaling, variational multi-scale, computational homogenization, multigrid homogenization, numerical homogenization, numerical upscaling, and computational coarse-graining, just to mention a few. Moreover, different definitions are used to indicate various scales. If the structure exists in two scales, however, the fine scale is often referred to as a micro-scale, unresolvable scale, atomistic scale, or discrete scale; the coarse scale is often defined as the macroscale, resolvable scale, component scale, or continuum scale. For more than two scales, the additional scales may be termed as mesoscales.

One alternative approach to the homogenization of artificial structures avoiding the limitations associated with earlier analytical homogenization models (Milton 2002) is the theory of a mathematical homogenization approach. It is based on the asymptotic expansion also known as two-scale homogenization, which is a well established concept in the theory of PDEs with rapidly oscillating periodic coefficients (Bensoussan et al. 1978). Its main advantage is that the method is generalized enough and unlike analytical techniques, can handle unit cells with inclusions of arbitrary geometry and any number of phases with no additional computational cost. Also, instead of formulating the problem as an eigenvalue problem, two-scale homogenization works directly on the original form of the governing equations and is therefore able to result in expressions valid for effective constitutive tensors.

In their studies, (El-Kahlout and Kiziltas 2011) further developed this approach by applying two-scale homogenization method to Maxwell's equations and

extracting the effective parameters of periodic dielectric and magnetic materials, that can be in their most generalized form lossy and are made of inclusions with arbitrary shapes and multi-phase material constituents. The numerical solution of the resulting PDE is carried out using a commercial FEA based solver, namely COMSOL Multiphysics, where the effective tensors are evaluated at a single frequency, for both isotropic and anisotropic effective material tensors with isotropic constituents. This is the first study where numerical material model based on two-scale homogenization is used to synthesize the microstructure of EM material with desired material matrices using formal design techniques such as topology optimization. Results of this design study are shown in Fig. 3.8 which was also fabricated (El-Kahlout and Kiziltas 2011) using novel Dry Powder Deposition techniques as demonstrated in Fig. 3.9.

Similar to EM materials, most heterogeneous materials, such as composites, polycrystals, and soils consist of constituents/phases with clear-cut boundaries that display different mechanical and transport properties. The use of homogenization of continuum allows a better understanding of the physical governing equations of individual phases, including their geometry and constitutive equations at the fine-scale phases, or at least a better grasp than at the coarse-scale phases. Put in other way, the process of homogenization provides a mathematical means by which coarse-scale equations can be deduced from well-defined fine-scale equations. Moreover it allows the determination of heterogeneous material behavior, at least theoretically without the need of testing, which is usually a very expensive endeavor. Also, through homogenization, one can estimate the full multiaxial properties and responses of heterogeneous materials, which present themselves as anisotropic materials and are most of the time extremely difficult to measure experimentally. In addition to describing the overall behavior of heterogeneous materials, the act of homogenization leads to local fields via the process known as downscaling given coarse-scale fields, phase properties, and phase geometries. This information is of critical importance in understanding and describing material damage and failure.
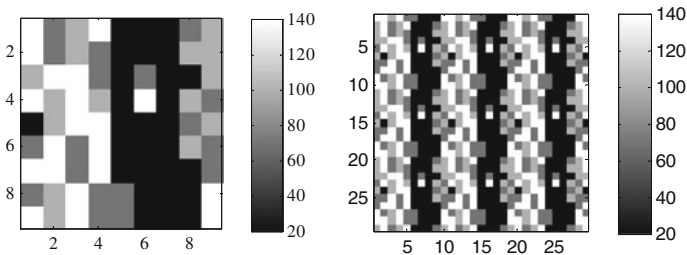
Fig. 3.8 Optimal material distribution (dielectric ranges from 20 to 140) of designed unit cell (*left*) and array (*right*) for a desired permittivity tensor of $\varepsilon = [45.0;'0.70]$ using mathematical homogenization and topology optimization.[reproduced courtesy of The Electromagnetics Academy]
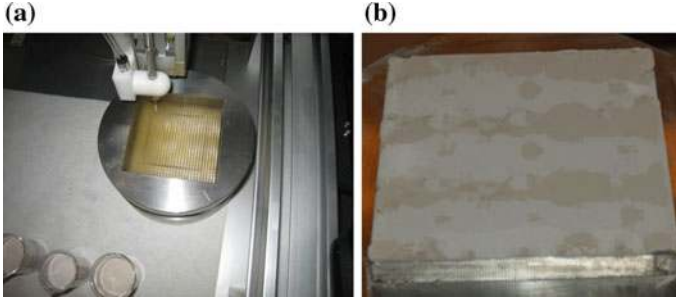
Fig. 3.9 Automated fabrication of design in Fig. 3.8 using dispensing machine within DPD in action (*left*) and resulting desired deposited substrate (*right*). [Reproduced courtesy of The Electromagnetics Academy]

3.2.6 Solid Mechanics

Two main branches exist within the application of the principles of mechanics to bulk matter: the mechanics of solids and fluids. When viewed from a global perspective, the common subject is that of continuum mechanics. More specifically, continuum mechanics conceives the useful model of matter as continuously divisible, and does not make any reference to its discrete structure at microscale, which is well below those scales of the phenomenon of interest. Solid mechanics is concerned with stresses, deformation, and failure of structures and solid matter. A material is called a solid and not a fluid if it is able to support significant amount of shear force over a certain time period of a natural process or technological application of interest.

The main equations of continuum physics can be presented by separating them into global and local laws. The former serve as the foundations of continuous media theory and are summarized here (Muntean 2015). In all these formulations, $\Omega'(t)$ denotes arbitrary configuration of partial volume B′ of B. More specifically, global balance laws for the five major conservation principles are presented here for mass, linear and angular momentum, energy, and entropy.

Mass:

The conservation of mass is expressed in its most general form as

$$\frac{d}{dt}m(\Omega'(t), \mathbf{t}) = 0 \tag{3.1}$$

for all $\Omega'(t) \subset \Omega(t)$, where $m(t)$ stands for the total mass in $\Omega'(t)$, i.e.,

$$m(\Omega'(t), \mathbf{t}) = \int_{\Omega'(t)} d\mu_{\mathrm{m}} = \int_{\Omega'(t)} \rho dx \tag{3.2}$$

with $\rho(\mathbf{t}, x)$ denoting the density. Assuming that there is no internal mass production, (3.2) states that the total mass of any material partial volume is conserved.

Linear Momentum:

The conservation of linear momentum or balance of forces is expressed in its most general form as: For every part $\Omega'(t) \subset \Omega(t)$ we have

$$\frac{d}{dt}\ell(\Omega'(t), \mathbf{t}) = \mathbf{F} \tag{3.3}$$

where the linear momentum can be defined via

$$\ell(\Omega'(t), \mathbf{t}) = \int_{\Omega'(t)} \mathbf{v}\,\rho dx \tag{3.4}$$

More specifically, the time rate of change of total linear momentum of *l* in B′ is equal to the force **F** exerted on B′. The force **F** consists of the contribution of the internal body forces per unit of volume $\rho\mathbf{f}_b$ and contact or surface forces per unit of area **t** acting on the boundary ∂B′ of B′. Here, **t** is the stress vector or traction.

Angular Momentum and Moment of Momentum:

The conservation of angular momentum or balance of moments is expressed in its most general form as

For every part $\Omega'(t) \subset \Omega(t)$, we have

$$\frac{d}{dt}\boldsymbol{\alpha}(\Omega'(t), \mathbf{t}) = \mathbf{M} \tag{3.5}$$

where the angular momentum can be defined via

$$\boldsymbol{\alpha}(\Omega'(t), \mathbf{t}) = \int_{\Omega'(t)} x \times v\,\rho\,dx \tag{3.6}$$

More specifically, the time rate of change of total angular momentum **α** of B′ is equal to the moment **M** of the force **F** exerted on B′.

Energy:

The conservation of energy balance is expressed in its most general form as: The time rate of change of the total energy within B′ which is composed of the kinetic energy *K* and internal energy *E* and is equal to the rate of work, say *P*, done by both the body force and the contact force, plus the heat supply *Q* from internal heat production and heat fluxes across the boundary of B′. So for every part $\Omega'(t) \subset$ (*t*), this can be written as

$$\frac{d}{dt}(K(t) + E(t)) = P(t) + Q(t) \tag{3.7}$$

where

$$K(t) = \int_{\Omega'(t)} \frac{|\mathbf{v}|^2}{2} d\mu_{\mathrm{m}} = \int_{\Omega'(t)} \frac{|\mathbf{v}|^2}{2} \rho \, dx, \tag{3.8}$$

$$E(t) = \int_{\Omega'(t)} e \, d\mu_m = \int_{\Omega'(t)} e \, \rho \, dx, \tag{3.9}$$

$$P(t) = \int_{\Omega'(t)} \mathbf{v} \cdot (\mathbb{T}\mathbf{n}) d\sigma = \int_{\Omega'(t)} \vec{f} \cdot \vec{v} \rho dx, \tag{3.10}$$

$$Q(t) = \int_{\Omega'(t)} f_{\mathrm{Heat}} \rho \, dx + \int_{\Omega'(t)} \mathbf{q} \cdot \mathbf{n} d\sigma. \tag{3.11}$$

In Eq. (3.9), e represents the inner energy density. The first term in $Q(t)$ accounts for the heat source. The measure μ_{m} in the equations of $K(t)$ and $E(t)$ corresponds to the mass measure associated with the material body B.

Entropy:
The entropy increase within B is greater than or equal to the internal entropy supply, i.e., internal heat source over θ, which is the absolute temperature, plus the entropy flux across the boundary of B′, which can be expressed as follows:

$$\frac{d}{dt}\left(\int_{\Omega'(t)} s \, d\mu_{\mathrm{m}} \right) \geq \int_{\Omega'(t)} \frac{f_{\mathrm{Heat}}}{\theta} d\mu_{\mathrm{m}} - \int_{\partial\Omega'(t)} \frac{\mathbf{q} \cdot \mathbf{n}}{\theta} d\sigma. \tag{3.12}$$

Here s represents the entropy density. It is explicitly noted that all conservation laws are in term of extensive quantities. More specifically, global balance laws can only be written in terms of extensive quantities. However, the intensive quantities are related to local balance laws expressed in terms of PDEs and inequalities as well as boundary conditions and can be derived based on global laws of the preceding section (Muntean 2015).

3.2.7 Fluid Mechanics

Various theories govern the physics of fluid mechanics and different methods are proposed and used in literature to provide numerical solutions/simulations primarily depending on the spatial and temporal scale of the phenomenon. Instead of going
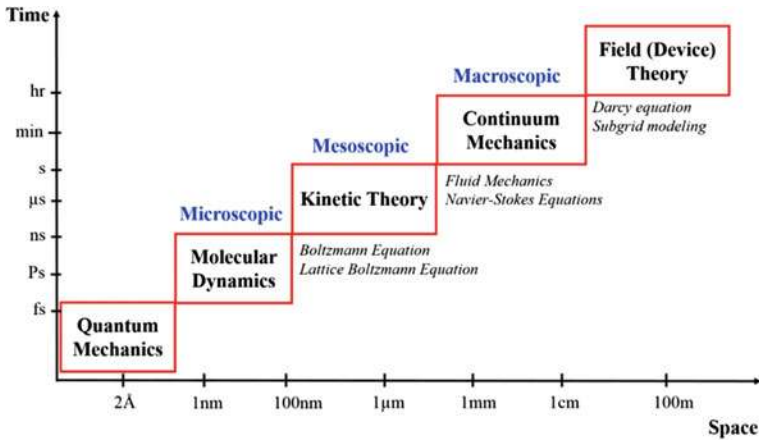
Fig. 3.10 Typical numerical methods used in fluid mechanics based on temporal and spatial scale

into detail with all methods, these theories and typical numerical methods employed according to the temporal and spatial scales are summarized in Fig. 3.10. As depicted in the graph, continuum mechanics prevails for above microscale and below tens of meters with a time scale between 1 s and hours. When the continuum assumption breaks down, the fluid has to be described by an atomistic point of view, such as the molecular dynamics as a microscale method or statistical rules govern the molecular group behavior, i.e., kinetic theories as mesoscopic methods for larger scales. On the spatial and time scale limit, if the characteristic length is smaller than 1 nm or the characteristic time is shorter than 1 fs, the quantum effect may not be negligible for the system of interest and quantum mechanics has to be brought into describe the transport. In fact, modeling at a smaller scale may present a more accurate description of the problem, but is likely to cause a much higher computational cost. Therefore, as always in numerical simulations, in engineering an appropriate tradeoff is considered when trying to determine in an accurate and fast way, the fluid behavior of interest.

Despite the emergence of high-speed platforms and the advances in efficient and accurate numerical methods, some computational fluid dynamics (CFD) problems still present themselves as challenging problems for the practical solution via numerical simulation techniques. For example, NASA has recently modified its aerospace design codes for earth science applications, thereby speeding up super-computer simulations of hurricane formation (Kazachkov and Kalion 2002). An example of such a CFD simulation using a 512-processor supercomputer is referred to in (Kazachkov and Kalion 2002). More specifically, actual data from a variety of different sources and climate models were integrated to generate high fidelity simulations so as to reproduce a hurricane forming in the Gulf of Mexico. As a result, engineers were able to simulate the formation and movement of a hurricane. However, the weather forecast of global earth based on CFD atmospheric and ocean

simulation is still a challenging problem, and calls for even larger amount of computing power and more accurate data. Overall, this is a multi-phase CFD problem with very complex geometry and dynamic boundary conditions.

3.2.8 Electromagnetics

In electromagnetics (EM), matrix systems with a few millions of unknowns known as dense matrix systems have been solved numerically for ten years now. Today, the number of unknowns that can be solved via simulations is on the order of a billion of unknowns (Gurel and Ergul 2007). This impressive improvement is attributed to the synergistic progress between hardware and algorithm design. It is also noted that for sparse matrix systems resulting from specific simple EM problems within electrostatic and magnetostatics, even larger scale problems can be addressed such as the World-record algorithm from Jülich calculating over three trillion particles (World-Record Algorithm from Jülich Calculates Over Three Trillion Particles—Research in Germany 2011).

As stated earlier, the physical response of many fields including EM, can be analyzed via differential equations. Therefore, PDE's were used for more than four centuries and continue to set the standard for modeling the physics of different media today. There are three main groups of differential equations, namely hyperbolic, parabolic, and elliptic, which describe fields with various physics. The Laplace equation or the Poisson equation given below is a well-known example of a generalized simple elliptic PDE. These are encountered in the numerical modeling of EM problems in the static regime and various transport problems. They are known for characterizing fields or potentials associated with no singularities distant from the source location, or equivalently these equations are differentiable functions and therefore do not allow for any singularity propagation.

$$\nabla^2 \varphi(\mathbf{r}) = -\frac{\rho(\mathbf{r})}{\varepsilon}. \tag{3.13}$$

Typical examples of parabolic equations, the second group of PDE's, are the Schrodinger and diffusion equations. These equations are characterized by their first time derivative and second space derivative. These are fundamental equations in quantum mechanics and heat transfer as well as low-frequency EM propagation in conductive media, respectively. A diffusion equation in standard form is

$$\nabla^2 \varphi(\mathbf{r}) - \frac{1}{c\,\tau}\frac{\partial}{\partial t}\varphi(\mathbf{r}) = 0. \tag{3.14}$$

The third class PDE's refers to hyperbolic equations, and an example belonging to this group is the wave equation. It has second-order space and time derivatives.

$$\nabla^2 \varphi(\mathbf{r}) - \frac{1}{c^2} \frac{\partial^2}{\partial t^2} \varphi(\mathbf{r}) = 0. \tag{3.15}$$

Solution of differential equations as earlier denoted are carried out by three major methods: a subspace projection method (e.g., FEM), the FDM, and the pseudo-spectral method. Various basis/interpolation functions are introduced to fit the unknown field (Chew 1995) in the subspace projection method. It covers a subspace of the larger space that the field is defined over due to the finite characteristics of basis functions. Thereby, the PDE is easily converted to a time dependent ordinary differential equation. For the solution of the equation via time stepping or marching, the derivatives can further be approximated using finite difference or the subspace projection method. Or as an alternative, time domain Fourier transform can be used to remove the time derivatives resulting in a matrix equation to be solved via iterative or inversion techniques.

A major alternative exists to the numerical solution of the governing Maxwell's equations in EM expressed in PDE. Specifically, initially a point source response called Green's function can be introduced. Based on linear superposition and as a result of an arbitrarily distributed source, the unknown field is obtained via spatial convolution of the distributed source expressed via Green's function. This corresponds to the equivalence principle (Harrington 2001) which allows the field in a given region to be expressed as Green's operator acting on the sources. Hence, the resulting equations are of integral equation type (IE). When compared with PDE, IE have an important advantage where the EM unknowns correspond to only surface unknowns, or to volume unknowns that occupy only a spatial finite region. Therefore, the number of unknowns in the IE formulation may be much less than those in the PDE formulation. More importantly, this IE formulation leads to the automatic satisfaction of the radiation condition if a suitable Green's function is chosen. However, in the PDE formulation absorbing boundary conditions or the so-known boundary integral equations replace the radiation condition. Additionally, using the subspace projection method (Harrington 2001), these IE can be converted into matrix equations. Equivalently, operators of the integral are replaced with matrix operators. However, the matrix representation of Green's operator corresponds to a matrix system which is dense because of its non-local nature. Hence, the computational storage and operations such as matrix vector products with that type of a matrix system can be computationally expensive. In literature, some methods have been developed to overcome these expensive matrix solutions. These include fast Fourier transform based methods, fast-multipole-based methods, rank-reduction methods, the nested equivalence principle algorithm, recursive algorithms, etc. (Weng et al. 2001).

As a final class of numerical techniques for EM radiation and scattering problems, hybridized versions of the two main classes combining their advantages have been developed. The FE-Boundary Integral (BI) method is one of the most powerful techniques belonging to this class. More specifically, it offers the flexibility of the FEM to analyze structures with highly complex geometrical and material details
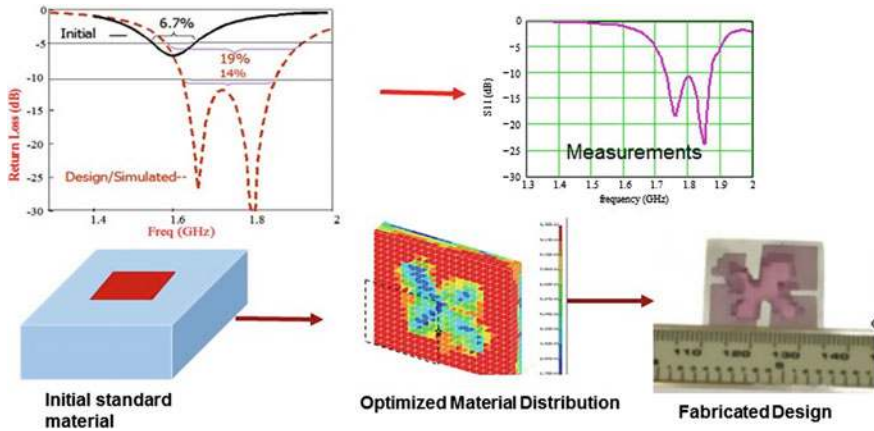
Fig. 3.11 Design results of novel material distributions of a patch antenna via integration of FE-BI method and topology optimization (Kiziltas et al. 2003)

but at the same time imposes a rigorous boundary condition via the use of the BI formulation. This tool's efficient and accurate analysis capability has allowed researchers to conduct numerous designs (Volakis et al. 2006).

It is especially noted that these efficient and accurate codes allowed for the first metamaterial-based antenna design using topology optimization based techniques as shown in Fig. 3.11 (Kiziltas et al. 2003). The design developed from scratch as shown in Fig. 3.11 was based on 5 individually textured layers which were also fabricated and measured. The agreement between measurements and calculations is truly impressive for the complex dielectric design. Above all, the threefold improvement in bandwidth is a clear demonstration of the remarkable potential of efficient and accurate numerical techniques in delivering novel designs not only in EM but also in other engineering disciplines.

Multi-scale problems as discussed in Sect. 3.2.5, present themselves in circuits, packages, and chips at various levels of complexity. Similarly, they exist also in antennas on complex platforms, in nano-optics and nanolithography applications. Therefore, multi-scale solutions of problems are critical for many applications. Similar to other applications, the size evaluation of the EM multi-scale problem is of great importance. More specifically, one needs to evaluate the multi-scale structures relative to the wavelength to determine which physics of the three to apply for their solution: circuit physics, wave physics, or optics physics. Avoidance or identification of ill-conditioned numerical systems plays a great role in the effective solution of multi-scale EM problems.

It is finally noted, that one of the biggest challenges today in the numerical solutions of EM problems is the model size of realistic problems which deems high-performance computing a vital necessity. Significant speedups have been achieved by hardware scaling and additional efforts have resulted in three main types of HPC platforms: (1) supercomputers, (2) computer clusters, and (3) cloud

computing. It is quite evident that, computational EM and large-scale computing will continue to evolve given that these are indispensable tools for EM analysis and design. Not only will it allow for efficient and practical performance evaluation and novel designs but it is expected to continue the enhancement of our thorough understanding of the physics within highly complex systems.

3.2.9 Multi-physics Methods

Many realistic problems present themselves as very complex problems due to their multi-physics nature. Scientists and engineers from various fields have been working on the combination of different numerical techniques with the goal of addressing these elaborate physical processes, such as the transition from continuum to discontinuum (e.g., fracture processes) or the interaction of multi-phases of matter (e.g., hydrofracture processes). As a result, a new class of numerical methods called hybrid/multi-physics methods evolved. It is due the developments in high-performance computing and computational science and computer hardware that this group of methods evolved. Major examples are: Combined Finite-Discrete Element Method (F-DEM), Hybrid Lattice Boltzmann-FEM, Lattice Boltzmann-DEM, etc. Areas of interest include algorithms and novel solutions for:

– Coupling of FEM and DEM simulations
– Coupling of FEM and/or DEM with CFD solvers
– Coupling of different solvers of continuum mechanics, e.g., FEM-FVM.
– Coupling of continuum and discontinuum mechanics solvers, e.g., FEM-DEM, FEM-MPM, FEM-LBM, etc.
– Coupling of solid and fluid mechanics solvers, e.g., FEM-LBM, FEM-FVM, etc.
– Coupling of discontinuum mechanics solvers, e.g., DEM-SPH, DEM-LBM, etc.
– Coupling of solvers for different scales, e.g., coupling of FEM-DEM.

3.3 Simulation of Machinery

In many simulation studies developers represent the components of the target system based on their dominant energy-based properties. Although various linear and nonlinear extensions exist, basic energy-based properties can fundamentally be given as inertia, storage (spring), and dissipation (damping). For example, in many engineering simulations a bearing is represented as a damping element and an axis slider in a manufacturing system is represented as inertia. It is also noted that a bearing component brings a negligible rotational inertia to the system as well as a slider which is somewhat flexible and its dimensions may change very slightly under heavy operating conditions. But these are not considered as dominant properties for these components.

The approach of representing complex and spatially distributed physical systems based on their dominant energy properties is known as the "lumped parameter modeling", implying the dominant energy-based characteristic(s) of a component are represented by using specific and predetermined elements (Karnopp et al. 2000). The use of lumped parameter systems approach results in a more structured approach of developing simulations for complex engineering systems. Using energy rather than other physical features (force, current, etc.) also makes it possible to use this approach in multi-domain systems.

3.3.1 Single Degree of Freedom Systems

Generally, in engineering, the classification of lumped parameter systems is given based on the number of the inertia elements. In many cases especially for mechanical systems, the freedom of motion of the component represented as inertia is important. For example, if a component can move in both x and y axis and/or can also rotate about z axis, these motion properties are all represented as separate inertial elements and flow variables.
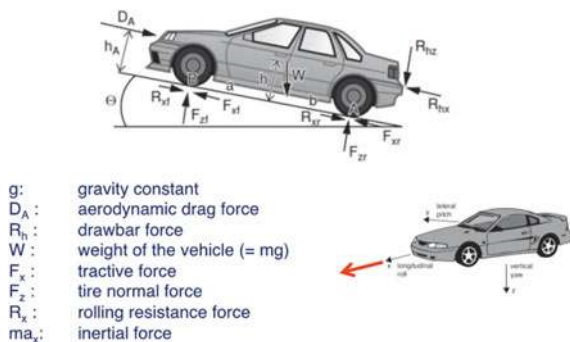
Single degree of freedom systems are systems represented with one inertial element and have one variable governed by fundamental physical equations. A good example for a single degree of freedom system is the longitudinal motion simulation of vehicles as shown in Fig. 3.12.

The system represented in this figure is given in (3.17) as a mathematical relationship (i.e., model) based on Newton's second law, where wheel traction forces, F, are the input and the vehicle acceleration, a_x, is the output.

$$ma_x = (W/g)a_x = F_{xr} + F_{xf} - W\sin\Theta - R_{xr} - R_{xf} - D_A + R_{hx} \qquad (3.17)$$

This mathematical model is straightforward to apply in simulation environments such as MATLAB/Simulink. The single degree of freedom longitudinal simulation can be used in basic fuel economy and traction (acceleration/braking) studies as

Fig. 3.12 Longitudinal motion of a vehicle

g:	gravity constant
D_A :	aerodynamic drag force
R_h :	drawbar force
W :	weight of the vehicle (= mg)
F_x :	tractive force
F_z :	tire normal force
R_x :	rolling resistance force
ma_x :	inertial force

reported in Rajamani et al. (2000), Ulsoy et al. (2012). However for many vehicle engineering studies such as axle-based traction control (Cakmakci et al. 2011; Dokuyucu and Cakmakci 2016) more complicated representations (i.e., higher fidelity simulations) that are also suitable for V-process development model discussed in Sect. 3.1 is needed.

3.3.2 Multi-Degree of Freedom Systems

One way to improve the fidelity of the simulations is to increase the degree of freedom of its underlying mathematical model. This can be done by increasing the number of flow variables representing the inertia element, or adding more inertia elements to the system simulation. As an example of increasing the fidelity of the model by adding new flow variables to the inertia representing is the half-car model for vertical motion given in Fig. 3.13.

In Fig. 3.13, the vertical motion of a vehicle is represented with two degrees of freedom (translation and rotation about the center of mass) rather than only the vertical motion of the mass of the vehicle. A detailed mathematical model describing this system can be found in ("Automotive Suspension—MATLAB Simulink Example," n.d.) 2017, using road elevations, q, as input and vertical movement of the center of mass, z, and body rotation, θ as outputs. With this representation in simulations, the vertical motion of the occupant area can be studied as well as the wheel based vertical road force, which is critical for traction control studies such as wheel-based braking, and acceleration with so-called load transfer.
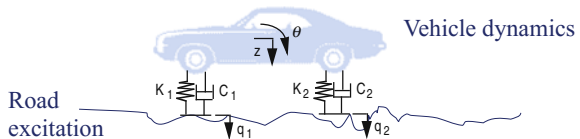
Another way of increasing the content is to increase the number of inertial elements considered in simulations. In this case, rather than using a single system boundary, where all of the components were lumped together before, can be broken into components and their relative interaction can be studied.

A good example for this kind of situation is the quarter car model shown in Fig. 3.14. In this model, a quarter of vehicle vertical dynamics is studied using quarter of the mass of the vehicle with the suspension system represented by k_s and c_s, f, tire parameters, k_{us} and c_{us} and vertical motion variables, z.
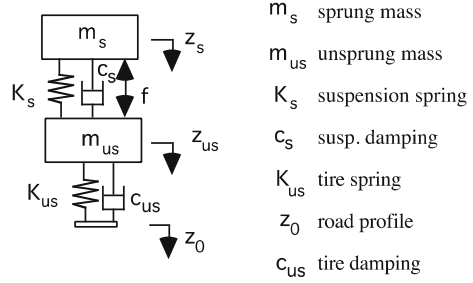
The mathematical equations representing this simulation is given in (3.18) based on Newton's second law:

$$
\begin{aligned}
m_s \ddot{z}_s + c_s(\dot{z}_s - \dot{z}_{us}) + k_s(z_s - z_{us}) &= -f \\
m_{us} \ddot{z}_{us} + c_s(\dot{z}_{us} - \dot{z}_s) + k_s(z_{us} - z_s) + c_{us}(\dot{z}_{us} - \dot{z}_0) + k_{us}(z_{us} - z_0) &= f
\end{aligned}
\tag{3.18}
$$

Fig. 3.13 Vehicle vertical dynamics

Fig. 3.14 Quarter car model
for vertical motion
simulations

|	
m_s	sprung mass
m_{us}	unsprung mass
K_s	suspension spring
c_s	susp. damping
K_{us}	tire spring
z_0	road profile
c_{us}	tire damping

It is important to note that by adding a new inertial element representing the mass of the wheel hub and suspension frame, the stroke motion of the suspension can be studied including the effects from the tire and the vehicle inertia which is not possible with the system given previously in Fig. 3.13.

The quarter car model given in (3.18) is an example of a multicomponent simulation in single axis of motion. More complicated models can be used to study wheel based multi degree of motion as given in Figs. 3.15 and 3.16 respectively for vehicle vertical motion (Rajamani and Hedrick 1995) and full vehicle motion.

In engineering simulation studies, as the number of components and the elements representing these components increase, the number of mathematical equations representing used in these simulations also increase. Therefore, the appropriate simulation content should be chosen to do the correct analysis with optimal computation time. For example, the full car model given in Fig. 3.16 is executed by solving 18 nonlinear equations per simulation step size as compared to the longitudinal model given in Fig. 3.12 contains only one ordinary differential equation. Both of the models can be used for fuel economy studies and both of them will contain uncertainties in inertia, spring and storage parameters.

Fig. 3.15 Standard half-car
model
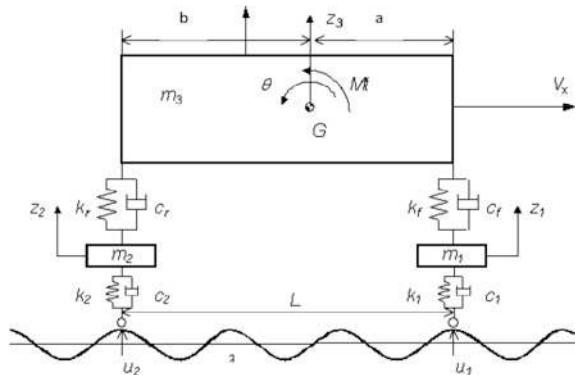
Fig. 3.16 Full car (18DOF) model
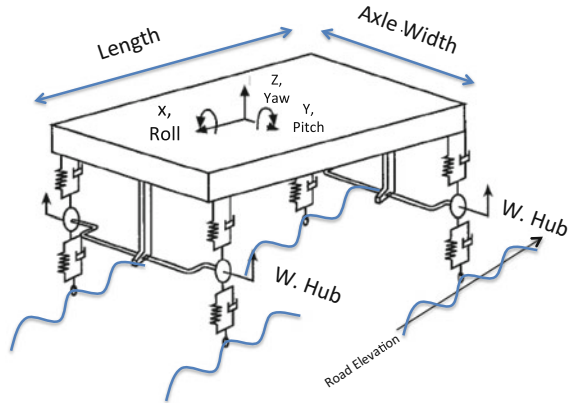
3.4 Simulation of Multi-domain Systems

In modern engineering systems, components that operate primarily in different domains (such as mechanical, electrical, digital) work together to complete complicated tasks. Therefore, a realistic simulation of the system should include the elements from different domains such as mechanical parts, power electronics to energize these mechanical parts, and digital components to monitor and/or control the operation.

Two representative cases of multi-domain simulations improving the performance can be given as the multi-domain simulations of electromechanical systems with controllers and online simulations to improve smart mechatronic/robotic systems.

3.4.1 Control Systems

Generally, algorithms in control systems are designed to have a certain dynamic behavior which can be represented in terms of a transfer function (in Laplace Domain) or a state space model (Ogata 1990). When these algorithms are actually implemented in actual systems their performance shows variations (usually degradations) due to the effect of execution in digital medium. These variations are due to the digitization of the algorithm, lack of realistic representation of the control system hardware and the effect of a communication in common medium such as networks.

Many control algorithms are developed by using a frequency or a time domain-based structured method based on their dynamic properties as discussed in many sources in control literature (Chen 1995; Ogata 1995). Once the development is finished, the resulting output is a fractional function that represents the input/output relationship of the control algorithm called controller transfer function,

C(s), where s is the Laplace variable. The dynamic controller relationship can also be represented by a matrix equation pair generally given in the form $\dot{x} = Ax + Bu, q = Cx + Du$ where u is the controller input, q is the controller input, and x is the controller states. These representations both imply a continuous system where calculations or events take place instantaneously using a specific order. However, when implemented in a real-time control system, algorithm computations take certain amount of time to finish before an updated command can be issued. For many systems with fast dynamics, the effect of implementation generates a deficiency in performance since the optimal performance was designed for a medium where events take place instantaneously.

More realistic and predictable results can be obtained by using discrete control systems that take into consideration of the digital timing in their formulation (Franklin et al. 2009; Ogata 1995). Algorithms can be designed and simulated as digital controllers using adaptations of the continuous methods. Alternatively, continuous controller functions can be digitized afterwards using simple methods. For example by using a direct conversion approach, a controller transfer function C(s) can be converted to its discrete version by replacing the s operator with $(z - 1)/Tz$ using a backward difference transformation. In this recipe z is the discrete variable and T is the sampling period.

Another important aspect of implementation of an algorithm in the digital world is the effect of *quantization*. Real numbers can have infinitely large digits during calculations, however for computers, it is more practical and maintainable to do operations in chunks of bits causing the calculations to take place in limited digits, which cause round off errors [Franklin et al.]. The effects of digitization and quantization can both be included in simulations to predict possible controller performance degradation in engineering systems.

Another important aspect in implementation of the control systemsis to include the hardware related properties such as un-modeled sensor/actuator dynamics ($S(s)$ and $A(s)$ respectively) and the effect of sampling as shown in Fig. 3.17.

In many controller development activities, the controller is designed based on the plant dynamics $P(s)$ only without including the sensor ($S(s)$) and actuator ($A(s)$) dynamics. The dynamic response effects provided by actuators and sensors can be included in simulations by using time delays, noise, and offsets. The effect of digital to analog conversion in the actuator is modeled as a zero-order hold (ZOH) element that keeps the value of the actuator output constant for one time step. This element also represents the fact that the actuator has internal dynamics and cannot change its output instantaneously. A sampler element is used at the sensor to represent the

Fig. 3.17 Feedback system with device boundaries and sampling
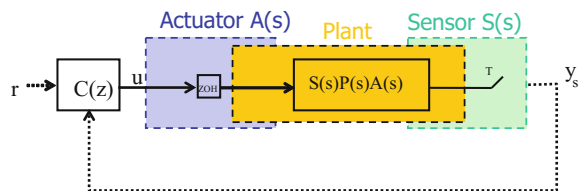
**Fig. 3.18** Dedicated digital communications (**a**) versus networks (**b**, **c**)
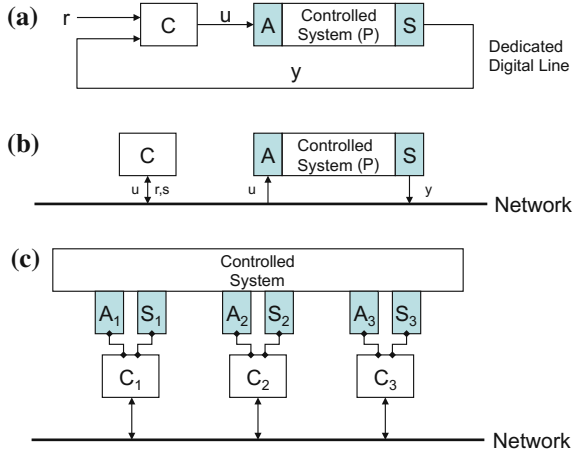
analog to digital sampling with rate T. This models the behavior of the sensor that it can only report plant outputs in every T seconds. Adding these effects to the overall simulation of the system provides more realistic performance studies.

Finally, in today's engineering applications, a common approach is to use communication networks instead of dedicated digital communication lines as shown in Fig. 3.18a, b. In fact, the benefit of this networked structure is being able to integrate as many components together with the capability of increased resources and easy maintenance as shown in Fig. 3.18c (Cakmakci and Ulsoy 2009). However, with the introduction of networks, the communication among system components can experience delays (or even loss of contact) as reported and studied by many researchers (Lian et al. 2002; Walsh et al. 2002). To remedy this effect, the overall system can be simulated using worst communication delays possible to measure the performance using step size-based delay elements and the controllers are calibrated accordingly.

3.4.2 Robotics and Cyber-Physical Systems

One of the important use of simulations that predict system performance after the product design phase is to employ them as observers and/or monitoring threads in actual systems running in parallel and making predictions/modifications to improve system performance.

A good example of this type of utilization is the *friction observers* in robotic locomotion devices such as the one developed in Ristevski and Cakmakci (2015) as shown in Fig. 3.19. Many non-wheeled robotic systems observe the friction force during translation. Inside the controller, a simulation of the whole system based on the dynamic force balance is run to predict the effective friction force called the friction observer. The friction predictions from this observer is used to update level
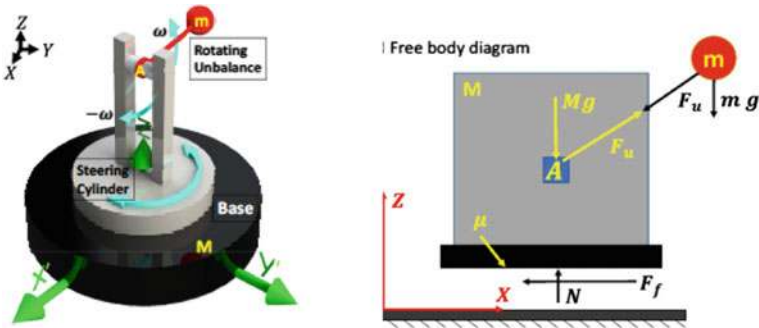
(a) Vibration based translational system
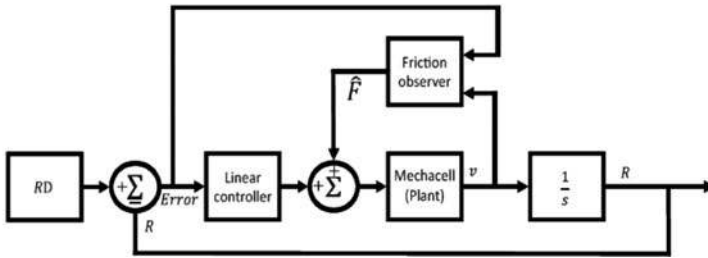
(b) Translation Controller using a Friction Observer

Fig. 3.19 Translating mechatronic device and friction observer

of the actuator force given to the system as an offset in parallel with its feedback controller so that the response performance can be improved almost 25%.

Another application of after-design simulation work in engineering systems is the pre-analysis and optimization of inputs embedded in computers of the manufacturing systems. Manufacturing of small parts can be costly and cumbersome since it often requires trial and error of adjustment of the machine settings. However, a remedy to this can be found by use of virtual iterative learning as reported in (Türeyen et al. 2016). A simulation of the additive-manufacturing system can be developed and used in parallel with a learning algorithm on the dimensional error of the final part before the real production is actually ran as shown in Fig. 3.20a. Researchers report using this method can improve the dimensional accuracy of a representative part up to 75% (Fig. 3.20b).

It is finally noted that similar to MDO based efforts for designing multidisciplinary systems such as automotive and aerospace products, there has been a continuous effort to design controlled mechanical systems using co-design strategies (Patil et al. 2010). The ultimate goal in these studies is to develop design frameworks that allow to reach system optimal designs from both the control and the mechanical design perspectives. Toward that goal, one such recent study is performed in (Kamadan 2016) where co-design strategies are proposed for robotic systems.
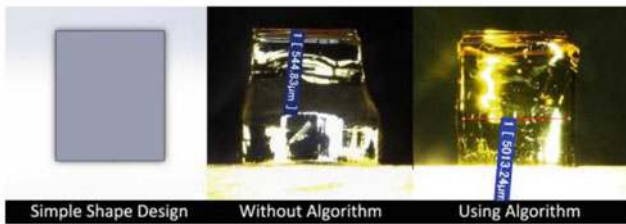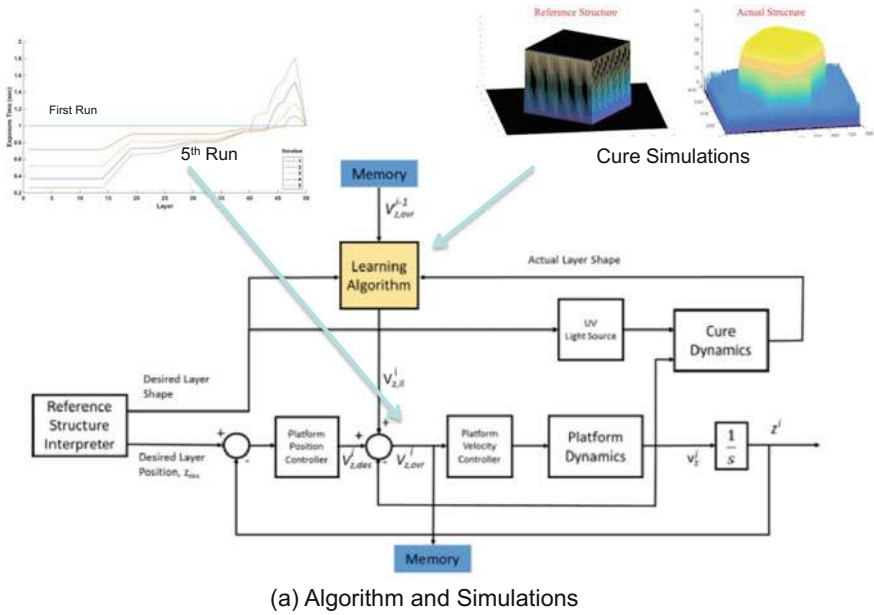
(a) Algorithm and Simulations

(b) Production Example

Fig. 3.20 Improving manufacturing quality with preproduction iterations

Robotic systems designed using domain-specific conventional approaches result in underperforming systems, i.e., are not system-optimal. This work introduces for the first time a unified framework of system-optimal designs of nonlinear controlled robotic systems driven by compliant actuators spanning a range of designs.

3.5 Conclusions and Outlook of the Topic

The ultimate objective within nearly all engineering projects is to reach a functional design without violating any of the performance, cost, time, and safety constraints while optimizing the design with respect to one of these metrics. Generally, in the beginning of each project, *wish list* like high-level requirements for the msyste

performance are specified. Then, high-level requirements are cascaded down to the lower levels of the system allowing systematic design steps to be applied to these well-defined engineering design problems. The resulting problems are concrete problem constructs that contain quantifiable performance and constraint metrics. In time, two primary approaches emerged for the solution of complex engineering design projects. With the early approach also known as the "Waterfall Design Process", the subproblems can be tackled and solved sequentially. In recent years, as an extension of "Waterfall Design Process", a new approach has emerged called the "V-model" where scalable and varying fidelity simulations plays an important role before the actual prototype of the system can be build.

A good mathematical model is at the heart of each powerful engineering simulation being a key component in the design process. These models can be obtained by using physics-based methods, empirical collections and analysis or a combination of these two for balanced fidelity and complexity. Another important aspect of developing simulations is its resolution, or in other words its building blocks. In the simulation of the continuum, systems can be built from their smallest elements using the most fundamental forms of the governing equations. Sometimes, a lumped parameter-based simulation of machinery approach can be taken to simplify the simulations and the forthcoming engineering work such as in the case of the model based control system design.

The introduction of efficient and powerful platforms enabled researchers to solve/simulate the constitutive laws of continuum in mechanics in combination with the laws of conservation of mass, energy, and momentum. The same is valid for other fields including fluid mechanics and EM. Some of the most popular methods used for this purpose are the Finite Element Method (FEM), Finite Volume Methods (FVM), Finite-Difference Methods (FDM), and Boundary Element Methods (BEM). These methods are applied to the simulation of matter in all forms, i.e., solids, liquid, and gas, based on a major assumption of continuum media, thus Computational Mechanics of Continua. Namely, continuum describes the non-separability of the considered domain and validity of continuity between any points in the domain so that differentiation is possible. Therefore, continuity between elements in any continuum based numerical technique is maintained as well.

Many realistic problems present themselves as very complex problems due to their multi-physics and multi-scale nature. More specifically, scientists and engineers from various fields have been working on the combination of different numerical techniques with the goal of addressing these complex and elaborate physical processes, such as the transition from continuum to discontinuum (e.g., fracture processes) or the interaction of multi-phases of matter (e.g., hydrofracture processes) at micro–macro scales. As a result, new classes of numerical methods called hybrid or multi-physics and multi-scale methods evolved.

In today's world, developing multidisciplinary systems such as for instance cyber-physical systems that consist of both mechanical and electrical components constitute a key part of the engineering projects. These types of systems contain software algorithms, digital sampling and power electronics, mechanical components as well as communication networks that have to be developed concurrently to

work coherently. This critical need for coherence has rapidly increased the importance of developing multi-domain simulations and engineers capable of supporting multidisciplinary analysis and design methodologies.

Review Questions

1. What are the primary phases of the engineering design cycle and how is simulation work used in each of them?
2. Name some of the numerical methods that exist to solve continuum problems.
3. Which type of problems can be classified as multi-physics and multi-scale continuum problems?
4. What challenges exist today when solving continuum problems?
5. What do all numerical methods suited to solve continuum problems have in common?
6. What are the effects of not-considering supporting hardware (networks, digital computers, etc.) to simulation performance in engineering systems?
7. What are possible uses for the simulations developed for the design cycle after product release to improve performance?

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Author Biographies

Melih Cakmakci is Assistant Professor of Mechanical Engineering at Bilkent University in Ankara, Turkey. He received his B.S. in Mechanical Engineering from M.E.T.U Ankara in 1997. He received his M.S. and Ph.D. in Mechanical Engineering from University of Michigan in 1999 and 2009 respectively. His research areas include modeling, analysis and control of dynamic systems. Prior to joining Bilkent University, he was a Senior Engineer at the Ford Scientific Research Center at Dearborn, Michigan, USA. He is a member of ASME, IEEE, and SAE.

Gullu Kiziltas Sendur is Associate Professor with the Mechatronics Engineering Program, Sabanci University. She received the B.Sc. and M.Sc. in Mechanical Engineering from the Middle East Technical University, Ankara, in 1995 and 1998, respectively, and the Ph.D. in mechanical engineering from the University of Michigan, Ann Arbor, in 2003. She was a Postdoctoral Researcher with both the Electro-Science Laboratory, Ohio State University and the University of Michigan. She also coordinated with the Ceramic Research Group, Material Science and Engineering Department, University of Michigan, on the advanced fabrication of dielectric composites. Her research efforts center on the design, analysis, and fabrication of complex engineering systems, such as miniaturized electromagnetic, electromechanical, and biomedical devices and multidisciplinary design optimization techniques. She has published a book chapter, numerous journal and conference articles and was honored with Career Award by TUBITAK (2007) and Young Scientist Award by the Science Academy of Turkey (2008). She is a member of the IEEE, ASME, and ACerS.

Umut Durak is a research scientist in the Institute of Flight Systems at the German Aerospace Center. He is also Adjunct Lecturer in the Department of Informatics at Clausthal University of Technology. His research interests include model-based simulation engineering, simulation-based systems engineering and ontologies in simulation. He received his BS, MS and Ph.D. degrees in Mechanical Engineering from Middle East Technical University (METU) in Turkey. He is a member of the Society for Computer Simulation International (SCS) and Arbeitsgemeinschaft Simulation (ASIM) and a senior member of the American Institute of Aeronautics and Astronautics (AIAA). And, he is a part of AIAA Modeling and Simulation Technical Committee and editorial teams of the Simulation: Transactions of the Society for Modeling and Simulation International; and the International Journal of Modeling, Simulation, and Scientific Computing.