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A survey of modeling and control techniques for Micro- and Nano-electromechanical systems

Antoine Ferreira * Sumeet S. Aphale

Abstract—In the current times, MEMS and NEMS form a major inter-disciplinary area of research involving science, engineering and technology. A lot of work has been reported in the area of modeling and control of these devices, with the aim of better understanding their behavior and improving their performance. This work presents a review of the emerging advances in the modeling and control of these micro- and nano-scale devices and converges on the exciting research in on-chip control, with a mechatronics and controls perspective and concludes by projecting future trends.

Index Terms—MEMS, NEMS, lab-on-a-chip, modeling, control

I. INTRODUCTION

Though micro-electromechanical systems (MEMS) and nano-electromechanical systems (NEMS) research has gained tremendous popularity and momentum in the past two decades, the potential of small micro-, nano- and even molecular machines was recognized by researchers, especially physicists and chemists almost half a century ago [1]. The race for miniaturizing had begun and finally in 1974, the term Nanotechnology was coined [2]. The development of ‘cluster’ science, [3], and the invention of the Scanning Tunneling Microscope, [4], in the early 1980s ushered the era of nanotechnology and the first book on this subject appeared in 1986, [5].

It is generally accepted that an electrostatically excited tuning fork employing field-effect transistor “readout” was the first operational MEMS device, [6]. Since then, the MEMS technology has progressed rapidly and in recent years specialized devices for applications such as blood cell separation and analysis are constantly expanding the boundaries of MEMS [7]. NEMS devices have also evolved since their first prototype was successfully demonstrated by researchers at IBM, [8]. Research aimed at developing specific sensor ([9], [10], [11]) and actuator ([12], [13], [14], [15], [16], [17], [18], [19]) technologies for improved MEMS and NEMS devices is ongoing. More details as to the current state-of-the-art for sensors and actuators can be found in [20].

Models that can capture the dynamic behavior of these devices can be of great help in understanding and improving their design and ultimately, their performance. Additionally, as with any dynamic system, a suitable control strategy could align the actual performance of these MEMS/NEMS devices closer to the desired objectives. Therefore, the two key avenues of current engineering interest that have the potential to significantly enhance MEMS/NEMS devices are: (i) modeling and (ii) control. Modeling techniques that lead to a better understanding of these miniature device dynamics are currently being sought after. Accurate dynamic models could lead to specialized control strategies that will in turn lead to major improvements in device performances. In the recent years, a lot of research has been reported in the area of modeling and control of MEMS and NEMS. This paper presents an overview of the emerging innovative modeling techniques applicable to these miniature devices. Different models are presented for system design and control associated with physical mechanisms, geometry/scaling issues or computational aspect for real-time control of MEMS with challenging issues in NEMS. It also reviews the recent advances in the control of MEMS and NEMS devices that have been inspired by the recent innovations in sensors, actuators, modeling techniques and control theory.

A. Organization

The remainder of this review is organized as follows. Section II presents an overview of the various modeling innovations that describe the behavior of MEMS and NEMS devices. Complexity in modeling is reviewed with respect to associated physical mechanisms, geometry/scaling issues and computational aspect to minimize the real time control issues. This section is further divided into two parts viz: (i) Modeling for MEMS/NEMS design (subsection II-A), (ii) Modeling for MEMS/NEMS control (subsection II-B). Section III will review the various control technique implementations and is divided into (i) Open-loop control (subsection III-A), (ii) Open-loop control with input pre-shaping (subsection III-B), (iii) Closed-loop control (subsection III-C) and (iv) On-chip control (subsection III-D). Section IV will present the possible future directions in modeling and control of MEMS and NEMS devices. Finally, section V will give the concluding remarks of this review.

II. MODELS FOR SYSTEM DESIGN AND CONTROL

Today, an abundance of commercial circuit and system simulation tools exist for electronic circuits and control system virtual prototyping. Microelectromechanical systems have been analyzed using the classical physical models or continuum theories for the mechanical (elastostatic or elastodynamic), the thermal (thermostatic), magnetic (magnetodynamics) and
the electrical (electrostatic) energy domains [22]. Naturally, the design of reliable actuating techniques requires simple but realistic dynamic models of the device, either in input/output or in the state variable form. Accurate models lead towards optimal system design, better performance, better understanding of the device, short development time, and consequently, lower cost of the device. Furthermore, due to the compact layout, manufacturing tolerance, modeling errors, and environmental changes, MEMS are subjected to parasitics and parameter variations. In order to better guarantee their stability and a certain level of performance, one must take into account these factors in the design of MEMS control systems. This section reviews the models for system design (subsection II-A) and control subsection II-B associated with physical mechanisms, geometry/scaling issues or computational aspect for real-time control of MEMS with challenging issues in NEMS.

A. Modeling for MEMS/NEMS design

1) Reduced-order Models: In higher level MEMS/NEMS simulation applications, the computational complexity of getting an output for a given input from the model is simply too high. Thus, model reduction involves reducing the computational complexity of the model by reducing the number of parameters in the original model. If the original model is described by linear ordinary differential equations (ODE) then a typical approach is to write down the algebraic relation in the frequency domain. Reduced order models (ROM) are cheap in terms of memory and computational time and are needed to perform fast and efficient system-level composite circuit for MEMS on-chip development. For practical implementation of feedback control design, the models need to be finite-dimensional. In [24], a reduced nonlinear model was linearized at multiple operating points in order to design a PID-controller tuned via LMI-theory. For MEMS, truncated low-order models can be established this way, using a summation over only selected operating points. In the presence of significant nonlinearities, which often is the case for MEMS, the simple truncated models tend to be too imprecise. However, the technique can be enhanced, by combining structure of the model with finite element analysis a novel way to perform unknown parameters identification. New technique by combining the Taylor series expansion with the Arnoldi method to automatically develop reduced-order models for coupled energy domain nonlinear microelectromechanical devices is given in [25]. Model order reductions via Arnoldi algorithm applied directly to ANSYS finite element models has also been reported [26]. In this work, the authors adopt a micro accelerometer as an example to demonstrate the advantages of this approach. An electrostatically actuated fixed-fixed beam structure with squeeze-film damping effect was examined to illustrate the model-order reduction method in [27]. Compared with the linearized model, these works show that the reduced-order nonlinear models can capture the device dynamic behavior over a much larger range of MEMS operation but stability preservation is not guaranteed and has a low accuracy away from the expansion point. Based on differentiation of the discretized Finite Element (FE) equations for parameterization of MEMS macromodels (see, Figure 1) the authors in [21] computed the governing system matrices as well as high order derivatives (HOD) with regard to design parameters by means of Automatic Differentiation (AD). While the above formalisms were developed primarily for numerical simulations, the possibility to create nonlinear parameterized models based on Karhunen-Loeve decomposition is proposed in [23]. This reduced order model is cheap in terms of memory and computational time and compatible with fast and efficient system-level composite circuit for on-chip feedback control. In the presence of significant nonlinearities, which often is the case for MEMS, the simple linear model order reduction reported in this section tend to be rapidly imprecise due to the vast amount of possible expressions of nonlinearity. General approaches are formulated in the following section for updating the parameters of systems governed by multiphysics equations using advanced optimization techniques.

2) Macromodeling: Several computer algorithms based on 3-D Finite Element Analysis (FEA) have been coupled to 3-D design tool to simulate MEMS, [28]. In order to alleviate the computational expense associated with the 3-D analyses, considerable efforts have been devoted to the development of reliable distributed reduced-order models (ROM) for MEMS, [21], [23]. As an illustration, model order reductions via the block Arnoldi algorithm with/without Taylor-series expansion directly to ANSYS finite element models have been proposed for MEMS accelerometers, [26], as well as electrostatically actuated fixed-fixed beam structure with squeeze-film damping effect, [29]. Furthermore, the authors in [30] demonstrated

![Fig. 1. Examples of mechanical nodal conventions. F and M are positive valued. (a) Beam in tension, \( F_{x,a} = -F_{x,b} = -F \). (b) Beam accelerating in x. \( F_{x,a} = F_{x,b} = F \). (c) Moment bending beam with positive curvature in y. \( M_{y,a} = -M_{y,b} = M \). (Courtesy of [21]).](image-url)
that the resulting ROM can capture the static/dynamic behaviors of the electrostatically actuated MEMS plate very well. Taking the analogy to electronic circuit design further, the next generation of MEMS system designers are starting to use composable MEMS models (macromodeling) [31] as the electrostatic torsional actuator shown in Fig. 2, [32]. It shows a mixed level damping approach where the torsional actuator dynamics is simulated by Navier-Stokes equation-based finite element modeling and the squeeze film damping by lumped-parameter modeling. The pioneering work in forming composable MEMS models is SUGAR from UC Berkeley [33], coventor ARCHITECT, [34], and NODAS from Carnegie Mellon, [35]. ARCHITECT and NODAS use Analog hardware description language (AHDL) descriptions, while SUGAR has its models written in MATLAB. In the later case, the performance of the tunneling MEMS sensor can be estimated and improved based on mechanical-level analysis by ANSYS and system-level analysis by MATLAB, [36]. A feedback control system with one zero and two poles has been synthesized, improving the dynamic range and the bandwidth of the closed-loop system (around 15 kHz).

Recently, MEMS design engineers developed a practical method that combines structure of the model with Finite Element Analysis (FEA) in novel way to perform system identification and identify the unknown parameters. The result was a lumped dynamical model of a MEMS device that can be used for the design of feedback control systems, [38]. In principle, any lumped-constant model can be described in this way, thus overcoming the most serious limitation of the equivalent-circuit modeling technique mentioned earlier. A likely reason for the popularity of this technique is that it makes possible to simulate MEMS using ordinary circuit simulators. An another modeling alternative is to use functional entities representing nanodevices in an object-oriented fashion, termed macromodeling. Macromodeling procedure for coupled-domain MEMS devices with electrostatic and electrothermal effects have been widely presented. Numerical simulation of the dynamics using hybrid BEM/FEM (Boundary Element and Finite Element Method) approach was presented in, [39]. Hybrid analytical/numerical macromodels for the substructures with regular geometry were generated by analytical method and the ones with odd geometry by numerical method [40]. These techniques were tested on a generic MEMS device, a microtweezer. The nonlinear tunneling mechanism and electrostatic actuation were linearized using small-signal approximation. It must be noted that exporting macromodels for MEMS simulation requires the interfacing of various commercial tools for CAD (e.g., SolidWorks<sup>TM</sup>), FEA, simulation of electronic circuits (e.g., AHDL/VHDL language), control systems (e.g., Matlab/Simulink<sup>TM</sup>), multibody systems (e.g., ANSYS/Multiphysics<sup>TM</sup>) and also the microfabrication processes. There are definite drawbacks, the simulation of HDL models or models written in other high-level languages is usually considerably slower than the simulation of equivalent models built into the simulator. Furthermore, it is noteworthy to discuss macromodeling applicability in conjunction with MEMS control design since realtime feedback control issues are still unsolved.

3) Multiscale Models: The ability to design reliable MEMS/NEMS devices demand new simulation capabilities due to the length and time scaling effects at nanoscale [41]. Combination of classical microforces phenomena with quantum fields and molecular considerations become key issues to the point that thermal fluctuation influences the NEMS operation. Furthermore, the roles of surface and defects become more dominant. Finally, the behavior of materials at nanometer scale begins to be atomistic rather than continuous. Taken together, it gives rise to anomalous and often nonlinear effects, i.e., nanomechanics (Casimir effect, van der Waals, charges quantization), nano-optics (charge transfer), electrostatic-fluidics effects (dielectrophoresis, electro-welting, electroosmosis), nanomagnetics (paramagnetism), and so on. The challenge now faced by NEMS designers is to bridge the different scales to a more general framework, which has been coined as multiscale modeling [42]. Conceptually, two categories of multiscale simulations can be envisioned: both sequential and concurrent.

(i) Sequential multiscale simulations
The sequential methodology attempts to piece together a hierarchy of computational approaches in which large-scales models use the coarse-grained representations from more detailed smaller-scale models. In doing so, the simulations
Fig. 3. A table showing the type of physical models, their features and the applications that are most suitable for respective modeling techniques (Courtesy of [37]).

are running independently of each other and a complete separation of both length and time scales are achieved [77], [73]. Some examples of sequential coupling show that to accurately model MEMS/NEMS devices at least three length-scales need to be explored: mesoscopic at the package level; microscopic at the actuator/sensor level and nanoscopic at the material level. Reliability of packaged polysilicon microelectromechanical systems involves the computational study of environmental effects to predict the long-term performance of MEMS packages at mesoscopic and microscopic length scales. The authors in [72] present a multiscale finite element modeling (FEM) approach coupled to Monte-Carlo (MC) analysis for MEMS failure prediction. In a same way, a predictive-science-based multiscale modeling and simulation platform is proposed in [78] to predict material performance issues, such as radiation, thermo-mechanical cycling and damage and fracture due to shocks. The computational coupling of the atomic-scale description of nanomaterials (Molecular Dynamics (MD) simulation) to microscale actuators designs (traditional finite difference (FDM) or finite-element modeling (FEM)) pose severe challenges. MD simulation cannot simulate the whole systems due to its prohibitive computational cost, whereas continuum FEM/BEM scales poorly with system size and only approximately account for effects at material interfaces. To remedy these inadequacies, several authors coupled FDM/BEM simulations to MD models whose underlying physics are derived from nanomechanics theory [51], [79], [80], nanoelectronic structure theory [59], nanofluidics theory [81], and molecular biology [74]. In overall, the sequential multiscale model showed good qualitative agreement with the experimental measurements but requires more refinement to achieve good quantitative agreement.

(ii) Concurrent multiscale simulations

The concurrent multiscale approach attempt to link methods appropriate at each scale together in a combined model, where the different scales of the system are considered concurrently and communicate with a hand-shake procedure. The literature contains numerous methods of concurrent coupling; (i) the
combined finite element atomistic method (FEAt), (ii) the material point method (MPM), (iii) the local quasicontinuum method (QC), (iv) the bridging scale method, (v) the atom-scale finite element method (AFEM), and (vi) coarse grained molecular dynamics (CGMD) [82], [41]. Molecular dynamics simulations are commonly used to investigate size-dependence of the elastic properties of the nano-scale silicon cantilevers [66]. It reveals that continuum mechanics modeling can still be used on nanoscale structures provided that the dependence of elastic constants on dimensional scaling is accounted for. At a larger scale Coarse-Grained Molecular Dynamics (CGMD) modeling have been developed [68] to describe the behavior of the mechanical components of MEMS down to the atomic scale. It builds a generalized finite element formalism from the underlying atomistic physics in order to ensure a smooth coupling between regions governed by different length scales. Various electrostatic models namely: the classical conductor model [71], the semiclassical model [83], and the quantum-mechanical model [51], are being used for electrostatic analysis of NEMS at various length scales. The design methodology facilitates, under restricted conditions, the insertion of quantum corrections to nano-scale device models, during simulation. In the case of NEMS-based electrostatic actuation, Figure 3 shows the evolution of modeling theory w.r.t. device length scale : from classical continuum models to atomistic quantum mechanical models. In [37], a multiscale method, seamlessly combining semiclassical, effective-mass Schrödinger, and Tight-Binding Theories (TBT), is proposed for electrostatic analysis of silicon nanoelectromechanical systems. In [84], an integrated modeling methodology for nano-scale electronic devices has been proposed. This methodology includes domain-oriented approximations from ab-initio modeling and the selection of quantum mechanical compact models that can be integrated with basic electronic circuit or non-electronic lumped-element models. Finally, molecular dynamics (MD) and ab-initio quantum mechanics(QM) coupled to virtual reality (VR) techniques have been developed in [75], [76] for the prototyping of biological NEMS. The operator can design and characterize through molecular dynamics simulation, the behavior of bio-nanorobotic components and structures through 3-D visualization. In these works, the

<table>
<thead>
<tr>
<th>Length scale</th>
<th>Modeling</th>
<th>Key Ref.</th>
<th>Time scale</th>
<th>Computational complexity (*)</th>
<th>Computational error (%)</th>
<th>Modeling level</th>
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<tbody>
<tr>
<td>Macroscopic $L \geq 10\mu m$</td>
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<td>$1s \leq t \leq 10s$</td>
<td>$O(n^2)$</td>
<td>$~10 - 30%$</td>
<td>System-level</td>
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<td>Dynamical State-Space model</td>
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<td>Lumped Dynamical model</td>
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<td>High-Order Derivatives model</td>
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<td>Composite circuit macromodels</td>
<td>[33],[34],[35] [40],[39],[57]</td>
<td></td>
<td>$O(n^2)$</td>
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<td>VHDL/AHDL language</td>
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<td></td>
<td>Continuum Models</td>
<td>[58],[21] [42],[59]</td>
<td></td>
<td>$O(n^3)$</td>
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<td>Finite Element Methods</td>
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<td>Model Order Reduction</td>
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<td>$O(n^2)$</td>
<td>$~5 - 10%$</td>
<td>MEMS part-level</td>
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<td>Krylov algorithms</td>
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<td>Arnoldi algorithms</td>
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<td>Mesoscopic $100nm \leq l \leq 1\mu m$</td>
<td>Stochastic Methods</td>
<td>[62] [63]</td>
<td>$1\mu s \leq t \leq 1ns$</td>
<td>$O(n^3)$</td>
<td>$~25%$</td>
<td>Functional-level</td>
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<td>Direct Monte Carlo Methods</td>
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<td>[64],[65],[66] [67]</td>
<td>$1ns \leq t \leq 1\mu s$</td>
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<td>$~20 - 30%$</td>
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<td>Coarse-Grained Molecular Dynamics</td>
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<td>Stochastic Dynamics</td>
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<td>Atomicistic $1\AA \leq l \leq 1nm$</td>
<td>Density Functional Theory</td>
<td>[70] [67]</td>
<td>$1ps \leq t \leq 1ns$</td>
<td>$O(n^5)$</td>
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<td>Multiscale $1\AA \leq l \leq 100\mu m$</td>
<td>Continuum/MD coupled models</td>
<td>[71] [68] [72],[73],[74] [75],[76]</td>
<td>$1ps \leq t \leq 10s$</td>
<td>$O(n^5)$</td>
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<td>continuum/MD/QM coupled models</td>
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* where $n$ is the number of features in environment.
nonlinear continuum elastic theory, with material properties extracted from MD simulations, is combined with either the classical, semiclassical, or the quantum-mechanical electrostatic model and the continuum theory for the van der Waals energy domain to compute the self-consistent electromechanical behavior of biological NEMS. From the point of view of control, the concurrent coupling between the mechanical and the electrical energy domains at nanoscale necessitates a proper understanding of relevant physical theories for NEMS feedback control [85]. Actually, carbon nanotube-based NEMS devices (nanoswitch, nanotweezers) are actuated using analytical energy-based methods modeling (electrical capacitance model including van der Waals forces as well as finite kinematics) to predict the structural behavior and instability of the on/off states of the nanoswitch, or the open/close states of nanotweezers [42]. Recently, the influence of control parameters on the stationary oscillations of carbon nanotube-based oscillators via molecular dynamics simulations have been conducted [64]. The control of oscillator motion in the case of considerable fluctuations through the control force has been rendered possible. The methodologies reported here are completely general and as such are expected to be useful in the optimal control of nanotube-based NEMS devices.

4) Discussion: Table 1 gives a comparison table of various modeling technologies with its pros and cons. Methods used for simulation of several properties of MEMS/NEMS differ in their level of accuracy and in the computation time necessary to perform such calculations. Accordingly, the time scales that each of these methods can handle can be from a single total energy for the most accurate calculations, to picoseconds for ab-initio molecular dynamics simulations, and up to seconds for classical physics. The MEMS/NEMS design optimization requires a tradeoff between very accurate and computationally expensive descriptions of atomic nanomaterial phenomena and coarse system description avoiding prohibitively large computations. Classical continuum theories which are based on continuum assumptions are efficient and accurate at mesoscopic scale, but they may not be directly applicable for NEMS of nanoscale features. Atomistic simulation methods such as first-principles quantum-mechanical methods, molecular dynamics and Monte Carlo simulations are generally accurate for the mechanical analysis of nanostructures. However, the extremely high computational cost prohibits the application of the atomistic methods at the MEMS/NEMS device level. The unified multiscale approach can retain the accuracy that the individual approaches provide in their respective scales and provides a realistic modeling at the system-, MEMS part-, functional- and atomic-level.

B. Modeling for MEMS/NEMS control

1) Physical Models: Physicals methods for determining lumped dynamical models of thermal, piezoelectric, magnetic or electrostatic MEMS and NEMS devices for purposes of feedback control have been studied extensively in literature. Current modeling works are mainly focused on the empirical responses of the system dynamics, black-box models, as a practical model for real-time control, but offer minimal insight into the governing equations. System identification based on measured sets of input and output data obtained from exciting the system with pseudo random binary data (PRBS) gives a good fit to the measured data. The MEMS dynamics are dominated mainly by the first mode which can be accurately modeled by a mass-spring-damper second order-model, e.g. piezoelectric MEMS scanner [45], polymer MEMS actuators [48], piezoelectric microrobot-on-chip [86] and electrostatic MEMS vibrational gyroscope [87]. However, when the number of parameters grows, it becomes more difficult to span the complete parameter space, since each parameter lets the number of possible variations grow in an exponential way. As example, the fast dynamics of MEMS systems require higher-order models leading to complicated model-based controllers. As a more detailed approach, the gray-box models are developed for determining lumped dynamical models of MEMS devices, [52], [53], [54], for purposes of feedback control. A model consisting of millions of equations (e.g., a FEM model) is surely more difficult to handle and takes more time to solve than an analytic expression based on a simplified gray-box model. In [88], the authors determined a dynamical state-space model for control of thermal MEMS devices. The importance of temperature-dependent parameters was emphasized for dynamical modeling for purposes of feedback control. In [56], a computationally efficient model was developed for investigating the dynamics of the voltage-driven MEMS device embedded in a dielectric fluid. However, these models were partly based on physical principles while also relying on empirical results to define complex physical processes. Due to the compact layout [89], manufacturing tolerance [90], modeling errors [22], and environmental changes (e.g., adhesive surface interactions, and scale dependent material and thermal properties) [91], MEMS devices are subjected to parasitics and parameter variations. In order to better guarantee their stability and a certain level of performance, one must take into account these factors in the design of MEMS control systems. In the most complex form, white-box models with partial differential equations (PDEs), e.g., [55],[56], attempt to explain the underlying physics for the sensing and actuation responses of MEMS and NEMS. Nonlinear models based on finite-difference discretization of MEMS structures, e.g. lateral electrostatically-actuated DC-contact MEMS [53], and applying boundary conditions have been recently solved using a Gauss-Seidel relaxation iteration scheme. More efficiently and equally accurate during circuit simulation than PDEs, Volterra-series-based modeling describes the frequency dependence (e.g., the mechanical resonance) in combination with the nonlinear behavior of the MEMS variable capacitor [92]. As the complexity of such models involves model reduction techniques, there is always a tradeoff between accuracy of the model or possible range of application.

2) Advanced Modeling Algorithms: Recently, black-box advanced modeling algorithms of non-electronic parts has been introduced in MEMS modeling, so enabling radically faster simulation without concurrent algorithms and parallel computation, e.g. artificial neural networks (ANN), genetic algorithm
(GA) optimization, model prediction (MP), or fuzzy logic algorithms (FL). In [93], a lumped model of the capacitive transducer, being the part of a MEMS capacitive pressure sensing system, was created using an ANN. The ANNs here are considered universal approximators, convenient for black-box device modeling. A general approach was formulated in [30] for updating the parameters of systems governed by multiphysics equations using an optimization technique based on Genetic Algorithms (GAs). This approach was demonstrated on a MEMS micromirror which was governed by both structural and electrostatic physics. For systems with fast dynamics such as those in MEMS, a hardware embedded real-time implementation of model predictive control (MPC) has been investigated in [94]. The results show that MPC would be an appropriate controller implementation since the size and the application precludes the use of a dedicated computer. Finally, a method for reliability prediction was presented in [95], based on a combined fuzzy-logic and physics-of-failure approach. The specific case of a MEMS Fabry-Perot interferometer was analyzed and the failure rate estimations are discussed. Similar fuzzy logic control algorithms have been applied to optimally charge the microbattery of on-board MEMS sensors [96]. Recent manufacturing advances have opened the path for the fabrication of micromechanical devices and electronic subsystems under the same manufacturing and packaging process, thereby opening the path for the use of advanced modeling algorithms towards systems-on-chip applications.

III. CONTROL SCHEMES

Presence of sensor dynamics, fast high-frequency system dynamics and extremely sensitive system parameters make the control of MEMS devices a complex task. Over the years, researchers all over the world have come up with feasible control algorithms for MEMS devices. Based on these results, control techniques for MEMS can be grouped under three broad classes viz: open-loop control, open-loop control with input pre-shaping and closed-loop control, [97]. The choice of the control technique depends on various factors such as application, needed electronic circuitry, device dynamics, space constraints and sensor availability / implementation. The following sub-sections will review the various control strategies mentioned earlier. The section will close with a review of the on-chip control strategies that have been implemented by researchers so far, (Subsection III-D).

A. Open-loop control

During the infancy stages of MEMS technology, most MEMS devices were controlled in open-loop by applying very simple control inputs. This was mainly due to the relatively high speed of actuation as well as the inability of the then existing sensor technologies to procure noise-free sensory information that was unbiased by the sensor dynamics. Though advances in sensor and actuator technologies have further pushed the boundaries of accurate sensing at the micro- and nano-levels, successful integration of these sensors in MEMS remains an ongoing challenge, [20]. Recent advances have resulted in improving the traditional MEMS designs to achieve better dynamic performance under open-loop actuations, [27]. Open-loop control for large deflection electrostatic actuators was reported in [17]. In this paper the authors incorporated significant design improvements to the existing comb-drives designs [98], [99]. These improvements included reducing the actuator area by half, redesigning comb-teeth and suspensions to reduce side instability and using a launch and capture actuation scheme. MEMS deformable mirrors have been popularly controlled in open-loop, [100]. The open-loop scheme delivered accurate tracking to within 3% error. Wavelength-division multiplexed (WDM) routers with analog micromirror arrays were shown to operate in open-loop with excellent repeatability and stability, [101]. High repeatability and long-term stability of a MEMS wavelength selector switch in open-loop operation was demonstrated in [102], though it lacked a 100% add / drop functionality. A low-drift micromirror in open-loop control was demonstrated in [103]. Open-loop control of a MEMS deformable mirror using a non-linearly constrained quadratic optimization approach has also shown improvements in performance, [104]. In this case, with an a-priori knowledge about the aberrations in the target waveform, a quasi-steady state control was obtained. Though simulated results reportedly showed improved performance, practical implementation of this rigorously mathematical technique may be quite challenging. Recently, MEMS actuator designs are being modified to give better open-loop performance, [105]. An improved modeling technique that resulted in open-loop control of a tunneling accelerometer for very high resolution acceleration measurement was reported in [106]. In this case the tunnelling accelerometer was modeled based on a clamped micro-circular plate with a tunneling tip and the classic Kirchhoff thin plate theory was used for deriving the governing equations. A new hardware platform for tuning a MEMS based gyroscope in open-loop by measuring the frequency response of the device was reported in [107]. These platforms tuned the gyroscopes based on an evolutionary computational technique that improved the sensitivity of the gyroscopes and also enabled closed-loop operation. An open-loop technique to address the Sagnac effect in a fiber-optic gyroscope based on MEMS/NEMS fabrication has also been proposed in [24].

As problems such as inherent system nonlinearity, induced vibrations and effects such as stiction and friction cannot be completely addressed using open-loop control in many MEMS devices, input pre-shaping was seen as the next logical step in MEMS control.

B. Open-loop control with input pre-shaping

This technique relies on the fact that the static and dynamic behavior of many MEMS devices can be accurately modeled and in most cases, linearized. In this technique, the input signals are made more complex by shaping them in a way such that the adverse effects of the system dynamics are minimized (Ex: Bandlimiting the trajectory signal such that the natural frequencies/system resonances were not excited), [109]. For input pre-shaping, an accurate dynamic model of the system is of paramount importance, if any performance improvement is expected. An open-loop method that predicted
control voltages generating prescribed surface shapes on a MEMS deformable mirror was given in [110]. In this work, an analytic elastic model was used for the mirror membrane and an empirical electromechanical model was used for the actuator dynamics. Open-loop control with input pre-shaping has also been applied to control oscillations of MEMS based gyroscopes. For accurate angular rate measurement, the drive mode oscillation amplitude of the second mass has to be kept constant. By approximating the gyroscope by a lumped mass-spring-damper model and applying pre-computed actuation voltages, the oscillation amplitude can be kept constant as shown in [111]. For MEMS devices that involve multiple moving parts, such as MEMS mirror arrays, a feed-forward based control has been patented, [112]. This patent was specific to MEMS based, optical mirror arrays where motion of an active mirror has an aerodynamically disturbing effect on the neighboring static mirrors in the array. In this technique, feed-forward control signals with a normalized profile that minimized the aerodynamic coupling between the static mirrors were employed to cancel the induced disturbances. Feedforward control of a MEMS optical switch was reported in [113]. In this implementation, feed-forward was used to force the switch to reach the desired position in a fast and accurate manner with minimal overshoot.

Very recently, a patent was awarded for a input shaping actuation technique for MEMS devices, [114]. In this patent, a filtered voltage signal shaping technique has been demonstrated. This scheme is mainly useful in conjunction with MEMS devices that have micro-cantilevers and other vibrating elements whose natural resonances are minimally damped. The patent is based on results obtained in [115] by actuating a two-axis gimbal-less scanner using the open-loop with input pre-shaping technique presented in the patent. Filtering the input voltages may not always be feasible as it adds to either the system or the computation cost. Additionally, sub-optimal filtering may lead to unachievable slew-rates and supply saturation. It is the property of electrostatic MEMS actuators to generate a residual charge in their insulating layer that results in sticking of the electrode and increases response time. To prevent this sticking of electrostatic MEMS actuators and generate fast actuator response, an input pre-shaping technique was described in [116]. The patented technique of Input
Shaping was demonstrated to potentially nullify unwanted vibrations in MEMS devices such as MEMS optical switches in [117]. A similar technique was used in [108], to drive a micromirror to a desired tilt angle without residual vibrations, see Figure 5. The key advance in this input shaping technique was the inclusion of nonlinear system behavior, thus making it suitable for application in conjunction with a wide range of MEMS systems.

The inherent reliance of the input-preshaping technique on an accurate system model as well as a-priori information of the system behaviour limits the adaptability and robustness that can be built into this particular control technique. Finally, the combined advances in MEMS technology, sensor and actuator designs, system analysis tools and the ever-present demand to push the boundaries of performance in terms of speed, reliability and accuracy have led to the MEMS system be controlled by employing complicated closed-loop strategies [118].

C. Closed-loop control

Standard control techniques such as PID have been implemented on MEMS devices manufactured in bulk, such as MEMS based sensors and switches, [120], [121]. MEMS based sensors have been using closed-loop control for quite some time. Hitachi demonstrated a MEMS based closed-loop silicon accelerometer more than a decade ago, [122]. Closed-loop control was used for a MEMS micro-cantilever based pressure sensor [123]. In this application, an electromagnetic beam integrated onto a standard silicon pressure sensor diaphragm was driven to resonance using closed-loop control. As the diaphragm deflects under pressure, the stress in the beam caused a change in its resonant frequency. This change was found to be a highly sensitive measure of pressure [124]. This device offered wide dynamic range, high sensitivity, and high stability. It was also easy to be interfaced with digital compensation circuitry. Another successful application of closed-loop control in MEMS was reported in [125], where improving measurement accuracy was the main objective. Feedback control has been employed to accurately regulate the gap distance in an electrostatic MEMS based Fabry-Perot interferometer, [126]. In this implementation, a feedback circuit capable of sensing the property of the active device and providing an electrical stop when the minimum separation distance was achieved was integrated.

Closed-loop feedback control has been a common strategy to correct for machining imperfections in MEMS based gyroscopes. [127], [111] proposed active nonlinear and adaptive drive control approaches to compensate for errors due to device imperfections. Closed-loop tuning of a MEMS based gyroscope was reported in [107]. A custom-built integrated circuit that manages the signal filtering and provides real-time control for the JPL-Boeing manufactured MEMS based gyroscopes was reported in [128]. This technique used an ASIC that enabled the gyroscope to reject vibration disturbances and damped the transfer function by almost 40 dB. A US Patent for an application specific integrated circuit capable of exciting a selected gyroscope mode, induce damping and demodulate the signal containing the angular rate information to in-phase and quadrature components was issued, [129]. This circuit featured attractive properties such as low power consumption as well as ease of sensor integration. A dual-stage control algorithm that provided on-site identification of imperfections based on the dynamic response of the device and compensated for it using nonlinear electrostatic parallel plate actuators was proposed in [130]. In this paper, the authors first showed that using feedback alone to compensate for large structural imperfections (to the tune of 10%) would seriously compromise the device performance. Consequently they successfully employed a feedforward control loop to reduce large imperfections and combined it with a feedback loop to compensate for the device non-idealities and perturbations. [131] presented a novel architecture for the digital control of MEMS based gyroscopes. Digital control was also proposed for performance optimization of a MEMS based gyroscope, [132]. In general digital control was shown to offer more flexibility in terms of algorithms as well as control parameters. FPGAs used in these implementations significantly speed up the development process due to their ease of programmability. Cross-coupling and fabrication imperfections are the major performance limiting factors in MEMS based gyroscopes. Adaptive control based on velocity estimation has shown promise in alleviating these problems and improve the overall performance of the gyroscope by achieving larger operational bandwidth, eliminating zero-rate output, enabling self-calibration and deeming the gyroscope highly robust to parameter variations, [133], [134]. To further improve the gyroscope performance by accurately estimating the unknown angular velocity, sliding mode control has also been formulated, [135], [136]. These investigations proved that though computationally intensive, both these nonlinear approaches could significantly enhance the device performance. Furthermore, they also showed that sliding mode control controller of the vibrating proof mass resulted in a better estimate of the unknown angular velocity than that of the model reference adaptive feedback controller. An active disturbance rejection control scheme was proposed recently to address issues such as mechanical-thermal noise, parameter variations, quadrature errors and the mismatch of natural frequencies between two axes, [137]. In this work the two main control problems addressed were the vibrating modes of the gyroscope axes and the time-varying rotation rate estimation. These major issues can also be alleviated using an adaptive control method based on Lyapunov functions, as demonstrated in [138]. A discrete time observer-based adaptive control algorithm for improved angular rate estimates has also been reported, [139].

Performance enhancement for a probe-based data storage system was reported in [140]. In this paper, the authors proposed a position control system that resulted in accurate positioning of the micro-cantilever probe over a particular sector of the data storage disc. Positive Position Feedback (PPF) control was implemented successfully to provide active damping to a piezoelectric MEMS acoustic sensor, [141]. A detailed comparison between open- and closed-loop control of a MEMS electrostatic comb drive was given in [38]. Model Reference Adaptive Control (MRAC) technique was...
formulated for tracking control of MEMS based comb resonators, [142]. A real-time implementation of this technique demonstrated its ability to handle multiple uncertainties in device parameters that occur due to machining imperfections. In [113], a linear feedback controller was used to shape the system dynamics in a MEMS optical switch, resulting in fast switching operation. Nonlinear control was also used in manipulating MEMS based mirrors for high tilt and pointing accuracy, [143]. In this application, digital implementation of a full-state feedback was carried out resulting in a substantial increase in the mirror’s angular operation range and a reduction in the long-term angular noise. Nonlinear sliding mode control applied to controlling the position of a lateral comb resonator has been simulated in [144]. A cooperative angle control scheme to reduce the output stable control time in MEMS optical switches was proposed in [145]. In one of the novel applications, feedback control has been employed to provide accurate input gains and implement signal up-modulation to a MEMS based high-performance operational amplifier, [146]. In this application, the input stage of the operational amplifier is a MEMS based variable capacitor that converts low-frequency input voltages to high-frequency AC currents, resulting in reduced offsets and low-frequency noise.

In most closed-loop control of MEMS devices, the control loop was implemented using external circuitry and computing facilities. In many cases, even the sensors were independent and not an integral part of the MEMS device. With improved fabrication methods, component densities on a chip have increased drastically and on-board sensors and power sources have become the norm, [147], [148], [149], [150]. Thus, the system-on-chip concept with on-chip control is now gaining popularity, [151], [152], [153].

D. On-chip feedback control: The current trend

The main advantages of on-chip feedback are: (1) improved linearity, (2) improved signal-to-noise ratio and (3) improved
accuracy due to ease of compensation for interferences and system dynamics. The vast improvements in MEMS design and fabrication have led to real-time on-chip feedback control being the current thrust of many research endeavors. One of the main control issues for on-chip applications is power generation. Electrical power is needed for the actuation as well as sensory systems used in MEMS. Generating this power efficiently within the given space constraints of a MEMS chip, without causing insulation, dynamics or interference problems is a major concern and research focus. Some on-chip power sources have been reported and various power generation schemes are being investigated, [149], [148].

Microfluidics is an area where real-time feedback has been applied successfully, [155]. Precise handling of microfluidics in continuous-flow by using a flow sensor to monitor and on-chip pumps with feedback control to regulate the flowrate was presented in [156]. Electrowetting-on-dielectric (EWOD) has been proposed as a method of actuation for on-chip droplet generation [157]. Due to its compatibility with miniaturization, simple device configuration and fabrication, capacity to generate large forces at microscale, and low energy consumption EWOD has gained popularity in microfluidic applications. To monitor droplet volume and control applied voltages for on-chip droplet generation of constant volumes real-time feedback control was necessary. A successful feedback strategy that resulted in automated volume-controlled on-chip generation of droplets was reported in [158]. To account for the uncertainties during droplet separation, an improved feedback scheme was proposed in [159]. In this work the authors combined voltage modulation, capacitance sensing and a discrete-time PID controller to obtain significant improvements in droplet volume uniformity when compared to open-loop and standard closed-loop techniques.

On-chip control has also been applied to MEMS based high-speed synchronous micromotors, [22]. In this work, on-chip VLSI drivers are used for various signal processing, filtering, computing, interfacing and amplification tasks and the control of micromotors is achieved by applying the proper phase voltages to the micromotor windings. The control technique also incorporates robust tracking and disturbance rejection. Nonlinear control of electrostatic MEMS using a novel integrated charge and position sensor was reported in [160]. This technique resulted in full gap operation and improved transient performance. The control technique showed on-chip implementation potential as it could use the local integrated circuit components and the required sensor was easy to fabricate, did not increase device footprint and had negligible effect on the device dynamics. The design of an on-chip CMOS potentiostat was reported recently, [161]. The potentiostat was mainly developed for controlling the volume of conjugated polymer film used in microactuators. This on-chip mechanism was proposed for controlling microactuators used in cell capture microsystems.

With the advent of nano-electromechanical systems (NEMS), on-chip sensor technologies are being revolutionized, [154], [162]. As a result, the future is bright and holds exciting prospects for on-chip control of MEMS devices.

IV. A LOOK IN TO THE FUTURE

Nanometer scale actuators and sensors that can provide motion and measurement with nanometer-order resolution will enable new industrial applications in which only a few atoms or molecules are measured, transported, or processed. The design of molecular systems in which controlled linear and rotary motion can be achieved under the influence of an external signal is a major endeavor toward future nanoscale machinery. New and exciting phenomena have been observed in multi-walled carbon nanotubes (MWNTs), including field emission [163], quantum conductance [70] or constant-force nanosprings [164]. Based on these effects,
nanoscale linear servomotors with integrated position sensing have been investigated from experimental, theoretical, and design perspectives. Fennimore was the first to show an electromechanical actuator based on MWNTs [165]. Actuation experiments have demonstrated the feasibility of a prismatic nanoservomotor with integrated position sensing based on field emission [166]. The complete extension of the inner core is observed and the electrostatic force is calibrated to be tens of nano-Newton for individual nanotubes 16.5 nN under a 30-V bias. Such nanotube actuators have mainly been designed for solid-state NEMS actuation where manipulation and assembly of nanoscale objects are required. For applications in nanomedicine such as novel drug delivery NEMS capable to perform controlled and targeted drug delivery into cells, performances of nanotube actuators are limited due to the operation of high electrostatic fields in liquid mediums [167], [168]. It is the reason why proteins represent fertile territory for nanoscale mechatronics that produce linear motions in liquid environments. As illustration, substantial progress in DNA actuated nanomechanical devices has been initiated [169] through controlled variations of the physiological medium (temperature, acidic concentration, salt, ionic level). DNA undergoes a substantial mechanical denaturing transition (A-T and G-C base pairs tend to unbind locally) at the origin of DNA actuated nanomechanical [170]. In approaches toward artificial machinery, a variety of molecular and supramolecular systems have been designed in recent years in which changes in shape, switching processes, or movements occur in response to external chemical, electrochemical [171], light-driven [172] or photochemical [173] stimuli. The control of chirality, being one of the intrinsic features of living nature, was the guiding principle in a synthetic endeavor that ultimately culminated in the control of molecular motion, e.g. chiroptical molecular switches and light-driven unidirectional rotary motors [174]. Controllable and reversible actuation of an array of micro-cantilever beams has been achieved under redox conditions when a monolayer of bistable linear motor molecules were coated on the beams [175]. Bridging the fields of biology and nanotechnology, the authors in [176] propose a novel concept of encapsulated DNA molecule acting as nanoscale actuator inside carbon nanotubes in a water solute environment. While fully servoed linear NEMS remain a challenge, these investigations demonstrate the possibility of fabricating linear servomotors with integrated position sensing for various future NEMS applications, e.g., untethered nanosystems propelled by magnetotactic bacteria [177], atomic force microscope (AFM)-based data storage [178] or on-chip temperature sensing and control for cell immobilization [179].

V. CONCLUDING REMARKS

This review tries to be complete in its general scope by reviewing most major works in the field of MEMS/NEMS modeling and control. Though it is impossible (due to the size and time constraints) to list every single work in a review of such a varied and dynamic field, the authors believe that this paper provides the reader with the most up-to-date information about the various advances that have taken place over the years in the modeling and control of MEMS/NEMS devices. With the advent of better, faster computing hardware and dedicated software, it will be prudent to say that the field of MEMS/NEMS is bound to see an even greater influx of academic and industrial interest. As the fields of physics, chemistry, biology and mathematics evolve and fuse together, more realistic models that capture the behavior of these microscale systems most accurately should be a key result. This, in turn, will combine with the fast developments occurring in the areas of very high device density chip fabrications and flexible electronics to produce control techniques that will make the desirable performance of a MEMS/NEMS device easily realizable, robust and adaptive.

ACKNOWLEDGMENTS

The authors would like to thank all the past and present researchers in the field of MEMS/NEMS, control theory and modeling. This work would not be realizable without their efforts in the first place.

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