

Approaches and Perspective of Coarse-Grained Modeling and Simulation for Polymer–Nanoparticle Hybrid Systems

Parvez Khan,* Rahul Kaushik, and Abhilash Jayaraj

Cite This: *ACS Omega* 2022, 7, 47567–47586

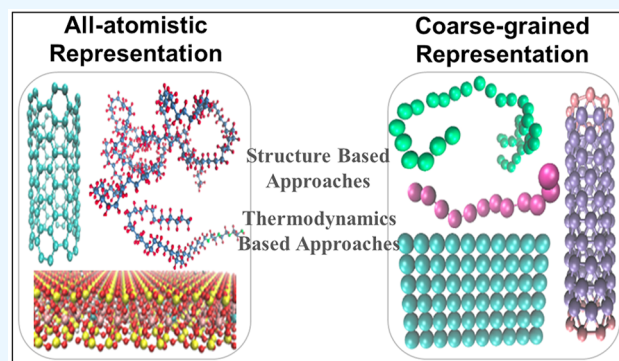
Read Online

ACCESS |

Metrics & More

Article Recommendations

ABSTRACT: Molecular modeling and simulations have emerged as effective and indispensable tools to characterize polymeric systems. They provide fundamental and essential insights to design a product of the required properties and to improve the understanding of a phenomenon at the molecular level for a particular system. The polymer–nanoparticle hybrids are materials with outstanding properties and correspondingly large applications whose study has benefited from this new paradigm. However, despite the significant expansion of modern day computational powers, investigation of the long time and large length scale phenomenon in polymeric and polymer–nanoparticle systems is still a challenging task to complete through all-atom molecular dynamics (AA-MD) simulations. To circumvent this problem, a variety of coarse-grained (CG) models have been proposed, ranging from the generic CG models for qualitative properties predictions to more realistic chemically specific CG models for quantitative properties predictions. These CG models have already delivered some success stories in the study of several spatial and temporal evolutions of many processes. Some of these studies were beyond the feasibility of traditional atomistic resolution models due to either the size or the time constraints. This review captures the different types of popular CG approaches that are utilized in the investigation of the microscopic behavior of polymer–nanoparticle hybrid systems. The rationale of this article is to furnish an overview of the popular CG approaches and their applications, to review several important and most recent developments, and to delineate the perspectives on future directions in the field.



1. INTRODUCTION

The organic–inorganic hybrid materials (i.e., polymer nanocomposites, biosensors, metal-impregnated polymers, fuel cells, solar cells, etc.) are of great importance today because of their enhanced mechanical, structural, thermal, gas barrier, and electrical properties, making them suitable for space application, automobile, electronics, consumer goods, health and medical, and food technology industries.^{1–10} The global aspirations are to search for some new organic–inorganic hybrids materials (such as polymer nanocomposites, functional nanomaterials, etc.) having properties that are optimized for some of the applications mentioned earlier. Especially, polymer nanocomposite materials (or organic–inorganic materials) are among the most studied advanced materials because of their enhanced properties (optical, electrical, gas barrier, thermal stability, mechanical strength, etc.); however, they are by no means completely explored. Polymer–particle hybrids represent an exemplary demonstration of the persistent and critical relationship between the structure and the properties in synthetic materials to deliver improved properties. It is demonstrated that the hybrid organic–inorganic materials play a pivotal role in developing the advanced functional nanomaterials that can be used for specific applications.

Discovery and development of the materials with experiment alone can be a tedious process and may require decades for such materials to be developed, tested, and manufactured to meet operational requirements.¹¹ Notably, the cost of the development of organic–inorganic materials is huge. On the other hand, computational approaches such as multiscale/CG simulation can help to design the hybrid organic–inorganic materials using fundamental science and engineering principles, can contribute significantly to their experimental development, and can save the high cost.

In principle, the polymer–nanoparticle hybrids are materials consisting of two or more dissimilar materials with well-defined interfaces. Among dissimilar materials, at least one remains one-, two-, or three-dimensional nanostructured (having structural features ranging in size from 1 to 100 nm).

Received: September 27, 2022

Accepted: November 21, 2022

Published: December 12, 2022



Depending on the strength of the interfacial tension between the polymeric matrix and the nanoparticles that could be modified, the resulting polymer–particle hybrids (e.g., polymer nanocomposites (PNCs), etc.)¹² exhibit enhanced properties. For instance, the molecular simulations and experiments have revealed that the morphology and properties of the hybrid materials depend rather considerably on the chemical details of the system,^{13,14} with solubility parameters for several hybrid components and length and density of the grafting polymer on the nanoparticle surface identified as the important parameters governing the hybrid morphology and properties.^{15–17}

1.1. Challenges in the Design of Polymer–Nanoparticle Hybrids. The major issues that need to be addressed in the context of polymer–solid hybrid materials are the variation in different properties (e.g., structural, dynamic, mechanical, thermodynamic, electrical, etc.) near to the interface compared to the bulk and the extent of these variations from the basal surface. For experiments, typically the challenges originate in the characterization of the structural, thermodynamic, and dynamic properties near the surface, which is either too small to be resolved via the experimental techniques or hidden by the bulk region. It is observed that the diffusion of nanoparticles within a polymer matrix is a long time scale phenomenon, and the exact mechanism of exfoliation is yet to be explored thoroughly. However, it is anticipated that the diffusion and dispersion of the nanoparticles within polymer matrixes is fairly related to the size of the nanoparticle, the aspect ratio and molecular weight of the polymer, and the nature of interactions between different components (e.g., monomer–monomer, monomer–nanoparticle, nanoparticle–nanoparticle, etc.) of polymer–solid hybrid materials. It has been successfully demonstrated that the management of the characteristics in subtle ways (i.e., molecular weight, aspect ratio, polarity, etc.) of the distinct components may lead to a synergistic enhancement in the properties of the hybrid materials.^{15,17} Therefore, a comprehensive understanding of the dependence of the overall morphology of the hybrid materials on the material characteristics and process parameters is very crucial for the systematic design of these hybrid materials to make the development timely and cost-efficient.¹⁸ It is anticipated that an improved understanding of the mechanisms at the nanoscale level could lead to the optimization of the processing variables at the macroscale. Industrial-scale production of suitable hybrid materials such as polymer nanocomposites is a big challenge as a result of the lack of experimental research in identifying the appropriate composition and combination of nanoparticles, polymers, modifiers, compatibilizer, and processing methodology. These parameters are very critical to develop hybrid materials (e.g., PNCs) with the required properties. To compensate the experimental effort, the application of computer simulation (such as density functional theory (DFT), molecular dynamics (MD), Monte Carlo (MC), statistical associating fluid theory (SAFT), self-consistent field theory (SCFT), polymer reference interaction site model (PRISM), coarse-grained molecular dynamics (CG-MD), etc.) techniques are being explored for the design of these materials. They further assist in a priori prediction/optimization of their structures and properties.^{19,20}

1.2. Computational Approach in Designing Polymer–Nanoparticle Hybrids. For addressing very basic issues such as the molecular origin of the reinforcement of nanoparticles in polymer matrixes—dispersion, fluctuation,

heterogeneities in mechanical properties, thermodynamics of the formation of hybrid materials, etc.—and the molecular origin with the dependence of rheological behavior upon the addition of nanoparticles in polymer matrixes, molecular simulations have been demonstrated and proved to be fairly useful. To this extent, the molecular modeling and simulation and polymer theories have made large contributions recently, but the former allows for more details on the chemical building blocks of the various components. Therefore, the development of computer simulation techniques for investigating and designing polymer–nanoparticle hybrids remains an active research field.^{18–20}

Many classical simulation models have been developed for capturing the various aspects of polymer–inorganic hybrid materials (e.g., PNCs). The polymer theories^{21–26} such as SCFT, DFT, and integral equation theory have made a significant contribution in predicting the equilibrium phase behavior, the thermodynamic tendency for the nanoparticle dispersion, and the macroscopic properties of polymer–particle hybrids, based on a mean-field approximation, but fail to describe the chemically specific nature of the nanoparticles and polymers.²⁷ DFT can provide the hybrid material structures in bulk to some extent and close to certain metal surfaces.²⁸ The MD simulations can furnish insights into the role of the solid surface in altering the polymer morphology. MD reveals more details at the molecular level and efficiently illustrates the chemical specificity of different components of the nanocomposites. The molecular modeling and simulations of different scales (from quantum to coarse-grained) have been indispensable tools for scientific research and engineering. These methodologies facilitate predictions and provide the understanding of experimentally observed phenomena such as the evolution of macromolecular structural, dynamic, and thermodynamic properties and microscopic and macroscopic material properties, which are important for the design of new materials. With the recent advancement in computational power, simulations of the polymer–nanoparticle systems can guide and complement *in vitro* macromolecular materials design and discovery endeavors. However, the long relaxation times linked with the polymer dynamics and the requirement of large system size for the anisotropic particles limit the utilization of atomistic resolution simulation on the polymeric materials. All-atom simulations have been utilized to simulate different polymer–nanoparticle systems. These simulations provide a good understanding of the interfacial behavior such as perturbation of the polymer structure (e.g., chain orientation, density, arrangement or wrapping of chains around nanoparticles, etc.), thermodynamics and dynamics of chains, and formation of glassy polymer layer around the nanoparticles but fail to investigate the long time scale phenomena such as the mechanism of dispersion or miscibility of nanoparticles in the polymer matrix.

The MD simulations with chemically specific force fields excel in investigating the effects of specific intermolecular interactions among the various components of polymer–particle hybrids. Several computational approaches have been established to examine the mesoscopic structures in polymeric systems including Brownian dynamics (BD), lattice Boltzmann (LB), dissipative particle dynamics (DPD), and time-dependent Ginzburg–Landau (TDGL) theory. However, the particle-based scale methods, including LB method, or DPD simulations have been utilized to explain the hydrodynamic

effects.^{29,30} The DPD simulations can help to understand the behavior of clusters of particles qualitatively. However, such simulation methods remain incapable of reproducing the structural properties of hybrid materials such as PNCs, while it is feasible with the CG-MD simulations.^{11,31} In CG-MD, one or more monomers/units of the hybrid materials are represented as a coarse-grained bead capable of reproducing parts of the polymer architecture. This leads to the loss of fine-grained atomic details of the system, which are crucial for studying properties and interactions of atom-level structures, but concurrently saves a significant computational cost by speeding up the simulation time through the minimization of degrees of freedom, simplifying the potentials, and allowing for larger time steps.

In recent years, the CG models have gained a lot of precedence in the field of MD simulations. The CG models could deliver a substantial alleviation of both the spatial and temporal limitations of all-atom models by averaging out some of the atomistic degrees of freedom. They perform better on reproducing the structural and thermodynamic properties.^{32,33,31} However, the coarse-graining schemes for reproducing the dynamic and transport properties are yet to be explored completely to achieve the state of the art for delivering the desired outcomes, and hence numerous research studies are in progress in this area.³⁴ In this context, the highly efficient CG models are required to capture the long time scale and large length scale phenomenon. For example, it can allow the dispersion of clay platelets within the polymer matrix to elucidate the synergistic effect and structure–property relationships of polymer–clay systems.^{11,32} In recent years, numerous modeling methodologies have been proposed to provide better insights into the nanoclay reinforcement physics. Zeng et al.¹⁹ provided an extensive review of the work that has been done in this field. In studying the system behavior of nanocomposites, MD has been the primary method of choice. Kuppa et al.³⁵ implemented MD simulations to study poly(ethylene oxide) (PEO)/nanoclay hybrid structures. They were able to correlate the results from the analysis with wide-angle neutron diffraction (WAND) and differential scanning calorimetry (DSC) studies of purely intercalated PEO in montmorillonite clay. Sinsawat et al.³⁶ utilized the CG-MD simulation to study the influence of polymer matrix architecture on nanoclay intercalation. Some simpler theoretical models are also proposed to explain the dynamics of melt intercalation in polymer nanocomposites.²¹

Notably, different types of CG models were utilized to investigate structure–property relationships in polymer–particle hybrid systems. In an oversimplified approach, the CG models are generally extended to explore the physics of particular systems and to more broadly delineate the fundamental characteristics of the systems. A further subcategorization into categories, including top-down, bottom-up, physics-based, knowledge-based, etc., also has been reported. Notably, some of these approaches can be classified into two groups, namely, generic and systematic or chemically specific. We believe that all of the approaches and subcategorizations have their own specific applications. Several reviews focusing upon CG polymer modeling have been made available over the last two decades.^{37–44} Considering the essence of revisiting the topic, this article is committed to dispensing an overview of the popular CG approaches for polymer–nanoparticle hybrid systems and their applications along with a review of several important recent developments

to particularize the perspectives on future directions in the field. It may be noted that the various methods discussed here are not exhaustive and do not cover all of the available methodologies, for which the reader's indulgence is sought.

Here, in the present review article, we predominantly focus upon the chemically specific modeling via bottom-up and top-down strategies. We will also discuss the importance of generic CG modeling (phenomenological approach). The first part of the article focuses on the various challenges in designing polymer–nanoparticle hybrids, the limitations of atomistic simulations, and the necessity of CG models for the hybrid systems. Next the article covers the methodological developments, applications, and limitations of the popular bottom-up and top-down CG strategies. The major points of discussion are the implementation of these CG models in reproducing or predicting the structural, dynamic, thermodynamic, and mechanical properties of hybrid materials. Further, we scrutinize the unsolved problems and prospects for CG modeling by spotlighting the potential of the methods to model the polymer–particle hybrid systems under diverse conditions. We believe this review article will be able to contribute to both new researchers who have been recently (or are planning to be) familiarized with CG modeling and seasoned veterans who stay tuned to the latest progress and perspectives in the field. Despite the comprehensive coverage, it was not possible to cover all of the relevant impactful work; therefore, we encourage readers to consider the presented review as a handy guide and the cited articles as a foundation stone to survey the primary literature.

2. COARSE-GRAINED MODELS FOR POLYMER–SOLID HYBRID SYSTEMS

The CG models for polymer nanocomposites were generally developed to reproduce the structural, dynamic, thermodynamic, and mechanical properties qualitatively and quantitatively. Therefore, these already developed CG models can be grouped into two main categories, namely: (a) generic coarse-grained models to determine properties qualitatively and (b) systematic or chemically specific coarse-grained models that predict properties of the specific system quantitatively. Chemically specific approaches are further categorized into two major approaches, namely, structure-based and thermodynamics-based approaches.

2.1. Generic CG Models for Polymer–Solid Hybrid Systems. The generic CG models can only predict the qualitative properties of the polymeric system instead of the quantitative measurement (such as extent of impact of temperature on the polymer mobility). They simulate the polymeric systems using a bead–spring model approach including the nonbonded interaction levels such as repulsive, neutral, or attractive.^{45,46} Figure 1 shows a bead–spring model developed for the polymeric systems.⁴⁷ Initially, the generic CG models were used to simulate the simple polymer–solid hybrid systems in which the polymer was near or confined between the planar solid surface.

Furthermore, the capability of the CG model was extended to more complicated systems such as polymer nanocomposites. The literature included numerous studies of a simple polymer–solid hybrid system, of which Bitsanis and Hadziioannou⁴⁸ were the first to successfully investigate the structure and microscopic dynamics in thin films of polymer melts confined between structureless, planar solid walls. They modeled the segments of the polymer molecules as point

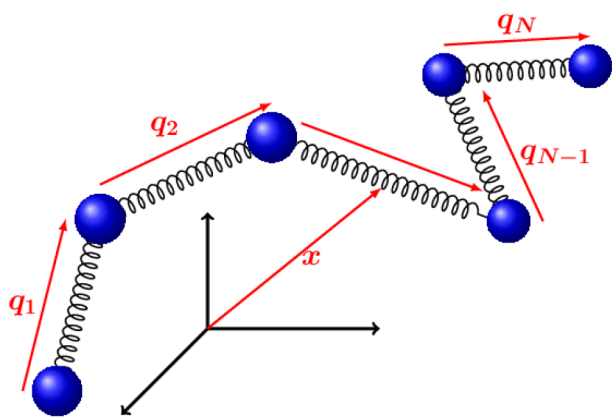


Figure 1. Depiction of the bead–spring model. Reprinted with permission from ref 47. Copyright 2018 Elsevier.

particles interacting with each other via a spherically symmetric, truncated, and shifted Lennard-Jones (LJ) potential. In a similar study, Matsuda et al.⁴⁹ investigated the influence of the surface topography and interactions on structural and dynamic properties of *n*-alkane chain molecules confined between solid interfaces. The polymer chain was assembled from mass points linearly connected by rigid bonds, which represented CH₂ units. The units of different chains and the units belonging to the same chain at least four bonds apart from each other were modeled to interact with each other via the shifted and truncated LJ potential. They observed an increase in layering of monomers as well as whole molecules near the strongly attractive surface, whereas the static behavior and dynamics of chains near the repulsive surface were similar to the behavior near the flat and structureless surface. In 2001, Aoyagi et al.⁵⁰ performed CG-MD simulation of a bead–spring polymer model confined between two solid walls and investigated the consequence of the interface on the chain relaxation by evaluating the time autocorrelation functions of the normal modes as a function of distance perpendicular to surface. They observed that the polymers near the walls are compressed toward the walls, and the influence of the solid wall on the polymer is observed up to a distance of ~ 1.5 nm ($\sim R_g$) from the wall surface. In another study, Mansfield and Theodorou⁵¹ performed dynamic CG Monte Carlo simulations on freely jointed model chain molecules in a cubic lattice near the solid surface. They determined the self-diffusion coefficient of chains and its spatial dependence. In all of the mentioned studies, the dynamic behavior of the polymer was investigated by calculating the mean-square displacement of the center of mass of the polymer segments (beads) as a function of simulation time. The chain mobility exhibited a dramatic reduction near the strongly adsorbing surfaces over several layers. For weakly adsorbing surfaces, these models predicted an enhancement in the polymer segment diffusivity due to the decrease in the polymer segmental density near the surface, as observed in real systems. A strong attractive interaction between the chain segment and the surface was also observed to appreciably prolong relaxation times in comparison to the bulk. These observations were in qualitative agreement with the behavior of all-atom simulation models. Polymer chain and segment dynamics near or in confined geometries is still a topic of interest that was studied broadly in the past through generic CG models.

Later on, the coarse-graining of the polymer melt near an adhesive solid substrate was conducted by De Virgiliis et al.⁴⁶ to investigate the other properties. They used various degrees of adhesion of the polymer toward the solid substrate and observed a slight decrease in the number of loops and trains with the increase in degree of adhesion; however, the average length of the trains and loops was found to be independent of the adhesion strength. Subsequently, in the case of more complicated systems, different bead–spring CG models were used to investigate the structural,^{52–54} dynamic, glass transition, and rheological properties of the polymer in the polymer–nanoparticle system. Grest used a simple bead–spring model to examine the miscibility of polymer-grafted nanoparticles in the polymer melt. A single nanoparticle in the polymer melt was simulated, and it showed the monomer layering to the vicinity of the nanoparticle, which was in reasonable accordance with the results of a more detailed, atomistic-level simulation. In contrast, autophobic dewetting of the nanoparticle was observed because of the transition of the stretched conformation to the collapsed conformation.⁵³ Afterward, Kalb et al.⁵⁵ investigated the effect of surface coverage and curvature of grafted nanoparticles immersed in an entangled polymer melt. The computational efficiency and simplicity of the bead–spring models allowed them to be utilized in studying systems with high molecular weight, such as entangled polymer chains close to a single-wall carbon nanotube (SWCNT), which are relatively hard to analyze using the full atomistic detailing methodologies.

In another study, Smith et al.⁵⁶ performed an MD simulation of model polymer–nanoparticle composites using a generic CG model to understand the modulation in viscoelastic properties of PNCs by focusing the interfaces of nanoparticle–polymers. It was observed that the nature of the nanoparticle–polymer interactions heavily affects the viscoelastic properties of the polymer matrix. Furthermore, a dense bead–spring polymer melt was investigated by Starr and co-workers⁵⁷ to explore the mechanism of clustering of the polyhedral nanoparticles in polymer melt, under both the quiescent and steady-shear conditions. In dispersed configurations, the shear viscosity was found to be higher as compared to the clustered configurations. This was in contrast to the stipulations derived from the macroscopic colloidal dispersions, and it was concluded that the variations of the polymer matrix properties in the surroundings of the nanoparticles could have resulted in this. In subsequent study, Shen et al.⁵⁸ implemented a bead–spring model to investigate the structural, mechanical, and viscoelastic properties of end-grafted nanoparticle-filled PNCs by considering the impact of grafted density and chain lengths. Their findings showed that the increase in the grafted chain length thickens the polymer matrix interface and improves the dispersion of nanoparticles (NPs). However, further enhancement in the grafting density facilitates the aggregation of NPs. The tensile strength of the PNC was also enhanced with the increase in grafted chain length. Furthermore, many simple bead–spring CG models were also utilized to demonstrate the impact of a solid surface on the glass transition temperature of a polymer near the solid surface.^{59–61} More literature indicating applications of the bead–spring CG models is available elsewhere.³⁷ The generic models were also implemented to explore the dynamics and entanglements of polymer melts consisting of an SWCNT. Karantanos et al.⁶² carried out a CG-MD simulation of polymer chains comprising the bead–spring chains of Lennard-Jones (LJ) beads in the

presence of an SWCNT, with or without attractive interactions, and observed more entanglement compared to a pure melt. Their results showed that the polymer mobility decreases near the SWCNT because of polymers in contact with the SWCNT. They showed that the entire polymer diffusion declines corresponding to its melt value, and this was due to the enthalpic interactions between the polymer beads and the SWCNT.

In another class of generic CG model that approaches the systematic model, Chakrabarti and Schweizer^{63–66} studied the polymer nanocomposite system by employing certain compressible free energy CG models derived from the traditional integral equation theories, viz., the microscopic polymer reference interaction site model (PRISM) theory to study second virial coefficients and spinodal demixing over a broad range of chain length, particle size conditions, and interfacial chemistry. The two different phase-separation behaviors, parted by a miscibility window, are commonly predicted for hard fillers. The study demonstrated that the nature and range of particle–particle intermolecular interactions significantly affect the contact aggregation, steric stabilization, and local and longer range bridging. They also described the application of this theory for systems having nonspherical, spherical, and polymer-grafted nanoparticles liquefied in the athermal and adsorbing concentrated solutions and the homopolymer melts. PRISM integral equation theory also helped in investigating the impact of local packing and the polymer–particle interfacial attraction on nanoparticle mobility.⁶⁵ These models accounted for the chains as the bonded sites that comprised a repulsive branch (usually hard core) and longer-range attractive interactions while interacting via pair decomposable site–site potentials. These models demonstrated some of the efficient qualitative insights into the structure and phase diagram of model nanocomposite systems, which may help narrow the gap to design fillers with specific thermodynamic stability and miscibility in polymer melts.

More recently, generic bead–spring models were widely used to investigate the different phenomena in model polymer nanocomposite systems. For instance, the bead–spring model based on the Kremer and Grest model⁶⁷ was implemented to explore the stress–strain nature of polymer nanocomposites filled with spherical nanoparticles. Hagita and co-workers⁶⁸ used the attractive and repulsive interactions of the nanoparticles with the polymers. Two different configurations of PNCs, namely, aggregated and dispersed, were used to examine the stress–strain behavior. The attractive interactions were observed to increase the stress values and the extent of nanoparticle aggregations. Bond orientations were also examined during elongation. For the large elongation ratios, the count of the aligned bonds along the elongation axis was found to be increasing. However, the correlation of the interactions was very small for the dispersed PNC configuration. Meanwhile, the increase in the aligned bonds was observed to be significantly correlated for the aggregated configuration. This demonstrated the significance of bound rubbers. Further, the nanofiller-filled cross-linked rubber model was studied to examine the effect of filler aggregation and filler–rubber bond on the elongation behavior of the rubber.⁶⁹ The results showed that, at large strain rate, the resulting stress enhanced with the elongation of the bonds of the polymer chain lying between the nanofillers. In another study, Furuya and Koga⁷⁰ examined the structures and mechanical properties of a disk-shaped nanoparticle-filled polymer nanocomposite

system through a CG-MD simulation. They used the Kremer–Grest model to describe both polymer and nanoparticles. Attractive interaction between the polymer and the nanoparticle beads was used to mimic the adsorption of poly(*N*-isopropylacrylamide) on the clay surface. Their results showed that a higher degree of polymerization is required for large fracture elongation, while the tensile modulus remains unaffected by the degree of polymerization, and these results were qualitatively in accordance with the experimental studies. Recently, Pasquini and Raos⁷¹ studied the morphology of a model polymer nanocomposite system using a bead–spring model. They concluded that well-dispersed and aggregated morphologies in PNCs can be obtained by tuning the interaction strength between the strength of the polymer and the nanoparticle.

The studies in the earlier discussion suggest that simple CG models can be efficient to study and predict the generic properties (e.g., dynamics, viscosity, T_g , etc.) of polymer–solid hybrid systems. Their computational efficiencies due to a simple form of CG bead–bead interactions can be counted as their major advantages. The bead–spring model was used to study the structure and dynamics in the thin film of a polymer confined between a structure-less, planar solid wall,^{48,72} the dynamics of short-chain systems along the adsorbing surface, and the spatial dependency of the self-diffusion coefficient of freely jointed model chains of the polymer near the vicinity of the solid surface.⁵¹ In all of the studies, the polymer dynamics were reproduced qualitatively and resulted in a considerable decline in the chain mobility along the adsorbing surface over many layers. Despite the advantage of computational efficiency, these models lack the link to specific systems. Therefore, a linking with an all-atomistic model/specific system requires a systematic CG model elicited straight from the chemistry of the molecules.

2.2. Chemically Specific CG Models for Polymer–Solid Hybrid Systems. In chemically specific CG models, the first task is the CG representation of the targeted system and then determining the suitable interaction between the CG beads so that the model can reproduce the targeted properties of the selected system. Typically, the systematic CG models are developed by eliminating the nonessential degrees of freedom and interactions from the all-atom level of models or a more fine-grained model designed to hold the critical chemistry of the system. To design the CG bonded and nonbonded interaction parameters, chemically specific or systematic coarse-graining approaches typically employ either bottom-up or top-down approaches or both. The bottom-up approaches utilize statistical mechanics to determine the CG interaction parameters from the atomistic simulation data. Hence, the developed CG models regenerate the thermodynamic and structural properties of the considered atomistic models. In contrast, the top-down approaches utilize the experimental data, rather than data from AA simulations, to design the interaction parameters.

Chemically specific or systematic CG models are effective to study the fundamental processes to investigate the unusual material properties, viz., mechanical strength, solubility, dispersion of nanoparticles, thermal stability, etc., of polymer–nanoparticle systems that might be difficult to calculate through all-atom simulation.^{37,73,74} In chemically specific CG force-fields, extensive information on the effective bead for the specific chemical composition is incorporated to facilitate the study of the effects of monomer–monomer and

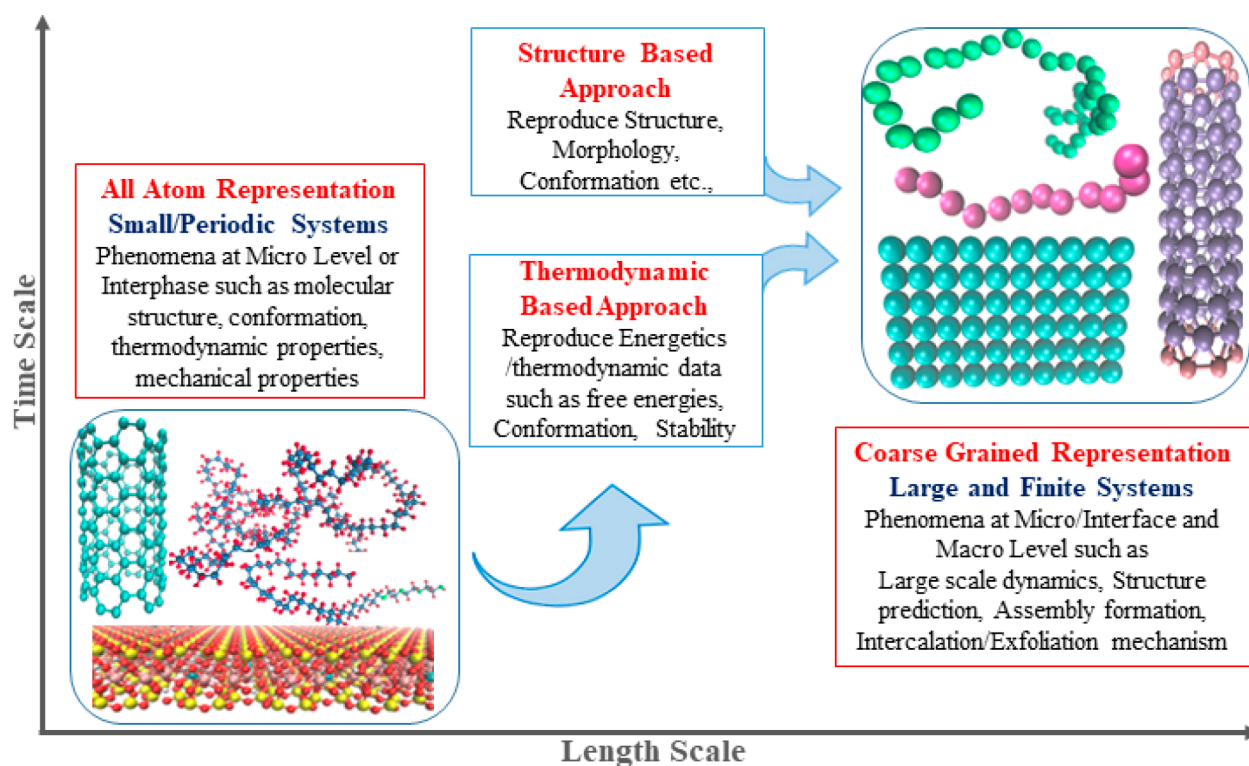


Figure 2. Schematic representation of the development of a coarse-grained model from an all-atom model.

monomer–nanoparticle interactions.^{75–80} The chemically specific CG models use effective CG potentials that are derived from the atomistic details of the particular polymer/molecule and map the groups of chemically connected atoms into “superatoms” or CG beads.^{81,82} The effective CG potentials among the CG beads can be derived through reproducing the targeted distribution functions such as radial distribution function obtained from AA simulation⁸³ or through determination of the potentials of mean force between CG beads⁸⁴ and through reproducing the experimental data (e.g., partitioning free energy).⁸⁵ The chemically specific CG models were quite successful in reproducing the structure and thermodynamics of a variety of systems quantitatively.^{11,31,32} These models were developed for a variety of polymer–particle systems using different techniques to determine CG parameters. For example, the bottom-up approaches, such as direct Boltzmann inversion (DBI), iterative Boltzmann inversion (IBI), inverse Monte Carlo (IMC), matching of potential of mean forces, force matching, and relative entropy minimization, utilize data from reference equilibrium atomistic simulation to generate effective CG potentials, whereas the top-down approaches, such as MARTINI CG models, use experimental data to parameterize CG potential. These models contain detailed particle geometry/structure and particle–polymer, particle–particle, and polymer–polymer interactions. These models have delivered considerable success to exploring the thermodynamics and structural conformations of several homogeneous and block copolymers, hybrid solid–polymer systems, and polymer nanocomposites quantitatively.^{11,31,32,78,86–91} These approaches preserve the intrinsic properties of the polymers (radius of gyration, density, diffusion coefficient, etc.).^{44,75,78,79,89,90,92–96} Thus, the interpartitions of CG models can directly correspond to the experiments. The mesoscale-based linking has been marked as

the foremost bottleneck for developing efficient multiscale frameworks in several studies, and the systematic CG approaches may deliver an alternative to these challenges.^{97–99}

In all types of simulations, the crucial features of the system are required to be retained while reducing the degrees of freedom. In addition, the CG models may be more beneficial in the simpler forms of interactions over the detailed models and deliver a better computational efficiency.⁸⁵ The system-specific CG models can vary in the extent of coarse-graining (the number of real atoms that correspond to one superatom) and the way of deriving the effective CG potentials. On the basis of the extent of coarse-graining, the systemic CG methods are roughly divided into three major classes: (i) low coarse-graining degrees, with one or two monomers in one bead, e.g., DBI and IBI schemes and MARTINI approach; (ii) medium coarse-graining degrees, having 10–20 monomers in one bead, e.g., blob model; and (iii) high coarse-graining degrees, having the whole chain mapped to a single soft colloid in a superatom. These variations impart an access to a broad range of time and length scales required to simulate the dynamic properties of the polymeric systems.⁹⁸

The coarse-graining of the polymeric systems from atomistic models has advanced, being primarily used for polymers in melt^{75–79} and in homogeneous environments.^{79,80} To model the polymer interactions in the proximity of solid surfaces, the CG simulation has also been applied. However, the extension of the systematic CG models to polymer–solid interfacial systems is a daunting research field due to the extra complexities imparted by the presence of interfaces. Therefore, only a handful of systematic CG studies are available for the polymer–solid multiphase systems, e.g., exfoliation of clay particles in polyethylene glycol polymer. On the basis of reproduction of the energetics and matching structural properties, a wide range of bottom-up and top-down strategies

to develop systematic CG models have been proposed. Figure 2 shows the schematic representation of development of a CG model from an AA model.

2.2.1. Structure-Based Coarse-Grained Models. A straight link to the chemistry can be achieved in structure-based CG models by structurally defined bonded and nonbonded effective CG potentials that are adopted from the atomistic model. These models delivered a successful quantitative study of the thermodynamics and structure, as well as conformations of diverse bulk polymer systems.^{75,76,78,79,96,100–102} As specified in the name, structure-based methods build the CG potential to reproduce a structural property of the all-atom system, viz., pair distribution function. The structure-motivated approaches are quite popular and include DBI, IBI, IMC, force matching (FM), and relative entropy framework methods. These structure-based CG approaches calculate the effective CG potentials from the systematic approximation of the many-body potential mean force (PMF). This approximation of CG potential, $U(R)$, adopts a widespread molecular mechanics in which the angles, bonds, torsions, and pair nonbonded interactions are modeled through a single potential that is a function of the corresponding mechanical degree of freedom. This may be characterized as

$$U(R) = \sum_i \sum_j U_i(\psi_i(R_i)) \quad (1)$$

where i indicates a particular type of interaction and j indicates the set of particles. The interaction potential, U_i , is a function of a scalar variable ψ_i , which itself is a function of the Cartesian coordinates, R_j . For example, if i represents the nonbonded pair interaction, then U_i will correspond to the pair potential, ψ_i will represent the pair distance, and R_j will be the Cartesian coordinates for a particular pair, j , of sites.

The iterative Boltzmann inversion (IBI) approach is among the most popular methods to reproduce the structural properties; however, many research studies also used direct Boltzmann inversion (DBI) to construct effective CG potentials for the polymeric systems with considerable success. The DBI approach furnishes the simplest and most straightforward way to determine the effective CG potentials from the atomistic distribution function.

$$U_i(r) = -k_B T \ln \{p_i(r)/J_i(r)\} \quad (2)$$

where i is a particular type of interaction (such as pair potential, bond potential, angle potential, etc.) modeled by U_i , $p_i(r)$ is the atomistic distribution function calculated for corresponding CG sites for the particular type of interaction determined at temperature T , J_i is the corresponding Jacobian factor, and k_B is the Boltzmann constant.

In particular, the DBI approach derives the potentials that deliver a reliable description for interactions that are efficiently characterized in the CG models. However, only a few chemically specific CG models based on the DBI approach have been proposed for the polymer–solid (organic–inorganic) hybrids.^{81,82,103–106}

Kremer and co-workers extensively used this approach to develop the systematic CG models for polymer melt as well as the polymer–nanoparticle systems. The chemically specific models have been used to develop a dual-resolution CG model to simulate bisphenol, a polycarbonate in contact with a nickel surface,¹⁰³ as well as the study by Huang et al.¹⁰⁶ on the CG simulation of poly(3-hexylthiophene) and fullerene mixtures.

However, none of these studies considered the surface structure. The interactions of polymer with the nickel surface were considered in the former study, while the fullerene molecule is accounted as a sphere estimated by a one-dimensional 10–4 repulsive potential of constant surface density in the later study.

Recently, the chemically specific CG force field for silica–polybutadiene interfaces¹⁰⁷ and the silica–poly(vinyl butyral) system¹⁰⁸ were developed using the DBI approach. The polybutadiene chain was considered through the united atom model, and the silica nanoparticle was accounted as a rigid body, implementing one Si-centered superatom for each silanol SiO₂ unit. The nonbonded interactions between silica and polybutadiene were adopted from Boltzmann inversion of the density oscillations at the model interfaces, extracted from atomistic simulations of the silica surface. However, no silica–silica interactions were used in the CG model; therefore, it might be possible that their model might not work if bare silica nanoparticle interactions have to be included. This model successfully reproduced the structural properties of the polymer near the silica surface. The dynamic and viscoelastic properties of the melt were also discussed in this study.¹⁰⁷ In another study, Walker et al.¹⁰⁸ examined the interfacial structure and adhesion properties of random-blocky poly(vinyl butyral-co-vinyl alcohol) (PVB) melts in contact with an amorphous silica surface, representing the interface found in the laminated safety glass. CG bonded potentials for the polymer chain were constructed via the DBI approach by matching the bond and angle distributions from all-atom simulations, while nonbonded interactions for the polymer were explained by the fused-sphere SAFT- γ Mie equation of state. The silica–PVB interactions were used in this study; however, silica–silica interactions were not considered. The DBI approach is helpful for the nonbonded pair potentials if the CG sites are dilute and for the bonded potential if the CG bonds are stiff. This measure depends on both the system and the CG mapping. Because the interactions in the CG models are generally linked, sometimes the potentials derived through the DBI approach do not reproduce the atomic distribution function, i.e., the radial distribution function (RDF).

Another popular structure-based approach is the iterative Boltzmann inversion (IBI) approach, a natural extension of the DBI approach to construct an effective CG potential from a set of known correlation functions, and it is quite successful for reproducing the structural properties of a system. The IBI approach has been remarkably successful for modeling complex liquids and polymers due to its simplicity in treating each interaction (U_i) and distance (r) independently. The IBI approach employs an iterative algorithm to extract an improved effective CG potential through comparing the probability distribution functions, $g_i^{\text{CG}}(r)$, obtained from the CG model with the corresponding target probability distribution functions, $g^{\text{AA}}(r)$, obtained from the atomistic simulations. The CG potential, U^{CG} , is improved according to the following iterative process.

$$U_{i+1}^{\text{CG}}(r) = U_i^{\text{CG}}(r) - k_B T \ln \{g_i^{\text{CG}}(r)/g^{\text{AA}}(r)\} \quad (3)$$

CG simulations are repeated to obtain the new pair correlations $g_{i+1}^{\text{CG}}(r)$, and this procedure is continued until $g_i^{\text{CG}}(r)$ reproduces $g^{\text{AA}}(r)$ as accurately as possible. The same process can be easily used to improve both bonded potentials.

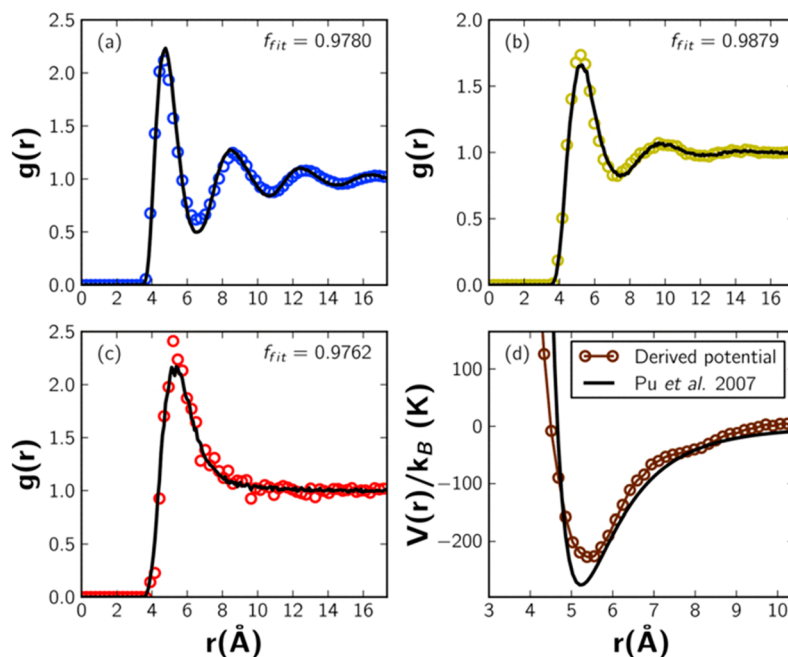


Figure 3. Depiction of the intermolecular bead–bead nonbonded interactions in the CG model obtained after using the multistate iterative Boltzmann inversion approach. Reprinted with permission from ref 111. Copyright 2014 AIP Publishing. (a–c) RDFs and (d) potential derived for propane using MS IBI. Panels (a)–(c) correspond to states A, B, and C, respectively.

Müller-Plathe and co-workers were the first to report the successful implementation of the IBI approach to construct the CG potentials for a polymeric system from atomistic simulation.⁹⁵ They designed an automatic iterative algorithm to construct the effective interactions that reliably mimic a set of target quantities derived from a reference all-atom molecular simulation. The differences between the potentials of the mean force calculated from the distribution functions produced from a guessed potential and the target distribution functions were used to refine the effective CG potential for a polyisoprene (PI) polymer melt as well as in solution successively. However, they stated that a unique CG potential will not work for different concentration regimes because the developed CG potentials essentially rely on the state of the polymer. Subsequently, the IBI approach was successfully used to develop a systematic CG model for a polymer in aqueous solution.^{109,110} Bedrov et al.¹⁰⁹ explored the structural properties of self-assembling poly(ethylene oxide)–poly(propylene oxide)–poly(ethylene oxide) (PEO–PPO–PEO) triblock copolymer micelles in aqueous solution using multiscale simulation. The CG potentials were determined using the IBI approach to match the targeted structural and conformational properties of polymers in aqueous solution adopted from the atomistic explicit solvent MD simulations.

Although the IBI approach has been predominantly used for simple fluids and polymer melts with the aim of reproducing the RDFs of the reference system in order to obtain nonbonded interactions,^{89,94,111,112} it has also been used for multicomponent (polymer–particle) systems. However, for the multicomponent systems, this approach shows a poor convergence performance. To determine the polymer interactions at the polymer–solid surfaces is a challenging task. Therefore, only a few chemically specific CG studies have been conducted on polymer–solid multiphase systems in the past decade.

A few chemically specific CG models have been proposed for polymer–solid (organic–inorganic) hybrids¹¹³ and polymer nanocomposites having nanoparticles (silica nanoparticles,¹⁰⁴ graphene,⁸⁸ and nanoclays^{11,32}). These chemically specific CG models used the IBI approach to obtain the interactions between CG beads. Chan and co-workers¹¹³ were the first to report the successful implementation of the IBI approach in constructing the CG interaction potentials for hybrid organic/inorganic molecules such as polyoligomeric silsesquioxane (POSS) tethered nanoparticles. The silsesquioxane cube was represented by eight CG beads, where the interactions of the CG beads were optimized to match the RDFs derived from the corresponding atomistic simulations of POSS nanocubes. They observed small aggregates of POSS molecules with similar local packings of the silsesquioxane cages and tether conformations in both the AA and CG simulations. Further, some researchers used the IBI approach to model polymer–nanoparticle systems. In these studies, the structure and dynamics of the polymer chain near the surface were investigated, and the conformation of the polymer chains was extended to report reduced dynamics of polymer chains/segments near the solid nanoparticle. Eslami et al.^{88,114} performed the CG-MD simulation of long chains of polyamide-6,6 confined between graphene sheets. The CG potentials were generated via the IBI approach by matching distribution functions for different degrees of freedom to the corresponding distribution obtained from all-atom simulations. The CG models successfully reproduced the layering of the polymer near the confined surface. In this study, they claimed that the CG interactions are transferable to a variety of systems and temperatures and are appropriate to simulate the confined polymer over a wide range of temperatures and intersurface distances. However, the graphene sheet–sheet nonbonded interactions were not included in their CG model. Subsequently, Ghanbari et al.¹⁰⁴ developed systematic CG potentials for a system of spherical silica nanoparticles (bare

and grafted) dissolved in atactic polystyrene via the IBI approach. They showed that the conformation of the polymer chains was strongly influenced by the presence of nanoparticles (NPs) and the extent of the structural perturbation depends on the type of nanoparticles: bare NPs versus polystyrene-grafted NPs. In another study, conformational properties and local dynamics of polyisoprene polymer chains near a smooth graphite surface were studied by a multiscale simulation¹¹⁵ where CG potentials were generated via the IBI approach.

However, it is observed that the developed effective potentials are limited by their nontransferability across thermodynamic state space and inability to capture thermodynamic properties correctly because the CG Hamiltonians are only parameterized to reproduce structural correlations appropriately.¹¹⁶ Although these derived CG potentials accurately reproduce the target RDFs, they are, in general, only applicable at the state point for which they were derived due to the nature of their derivation. Equation 3 clearly shows the explicit temperature dependence as well as the implicit temperature and density dependence through the $g(r)$ terms. For example, separate potentials were required to capture both the solid and fluid structures of a pure simple lipid.¹¹⁷ To address the temperature transferability of the CG potential, Moore et al.¹¹¹ proposed an extension to the standard IBI approach to improve the transferability of the derived CG potentials. This study showed that inclusion of target data from multiple states forces the IBI approach to sample regions of potential phase space that match the RDFs at multiple state points, thus constructing a CG potential that is more representative of the underlying interactions. The derived CG potential was less state-dependent and thus better suited than the standard IBI approach to simulate the systems over a range of thermodynamic states. Figure 3 shows the development process of intermolecular CG potentials from several iterations using the multistate IBI approach.¹¹¹ However, for complex systems, it may not be possible to optimize the potentials at a wide range of state points of interest, due to time- or length-scale limitations of the atomistic simulations, thus making it difficult to apply the IBI approach appropriately. Further, Maurel et al.¹¹⁸ also determined the effective CG interaction potentials for *cis*-1,4-polybutadiene polymer chains and silica surface from atomistic simulation using a bottom-up approach by employing the IBI method and investigated the structural and dynamic properties of polymer chains near the silica surface (bare and grafted) at different separation distances. Multiscale simulations have also been performed for the specific case of polymer silicate clay nanocomposite (PCNC)^{11,12,20,119} systems. To investigate the impact of the nature of the interactions among different components on nanocomposite properties, chemically specific CG models have proved extremely useful.¹²⁰ However, the IBI approach showed the issues of convergence while developing the CG potentials near the surface in highly heterogeneous systems such as PCNCs. In these systems, polymer molecules, adsorbed on the solid surface, interact with a large number of surface atoms, particularly in one or two directions at varying distances. Thus, the isotropic environment generally required in the IBI approach is not observed.³⁷ In a significant work, Suter et al. developed a chemically specific CG model for a montmorillonite–poly(ethylene glycol)/poly(vinyl alcohol) clay nanocomposite. Interaction potentials among the CG beads were generated by employing the IBI approach. Their model was able to provide a quantitative description of the dynamic

process of polymer intercalation into clay tactoids.¹¹ The CG potentials for the polymer were developed using the IBI approach, and nonbonded interactions between the clay particles were developed by matching the potential of mean force. The monomer density profile was used to determine the CG nonbonded interaction between clay and polymer, which indicated that the IBI approach is not enough to construct the CG potentials for polymer–nanoparticle systems. They also described the mechanism of exfoliation and dispersion of organophilic clays in hydrophilic polymer melts and determined the elastic properties of these nanocomposites. Their study showed that even a partial exfoliation of clay tactoid helps in significant enhancement of the Young's modulus of the nanocomposite, as observed experimentally.³² Recently, Volgin et al.⁶⁷ performed a CG-MD simulation to investigate the diffusion of fullerene nanoparticles in a polyimide R-BAPB melt. Effective CG interaction potentials for polymer nanocomposites were determined using the IBI approach. Their CG model excellently reproduced the structural properties calculated from the fully atomistic system; however, the local chain conformation in the CG model substantially perturbed the nanoparticle diffusion. They observed that the coarse-graining of the polymer chains on the length scale of the nanoparticle size contributes to a complete suppression of the sub-diffusive regime identified in the all-atom simulation. More recently, the IBI approach has been used to generate the CG models of silica nanoparticles in a polymer matrix. The CG model of a silica nanoparticle-impregnated *cis*-1,4-polyisoprene polymer was built to study the effect of nanoparticles and cross-links in the uniaxial tensile simulation.¹²¹ The results of this study showed that the polymer-grafted silica nanoparticles and the cross-linked structure play reinforcing roles, while the smooth nanoparticles do the opposite, which was in line with the experiment results. Further, the same group investigated the effects of silica/carbon black hybrid nanoparticles on the viscoelastic properties of uncross-linked *cis*-1,4-polyisoprene rubber.¹²² The CG potential interactions for the system were derived via the IBI approach. In another study, Shere et al. developed the CG potentials between various silica species formed during silica polymerization via the IBI approach in order to understand the molecular transformation of silica aggregates during polymerization.¹²³

Despite the success of structure-based approaches such as IBI and DBI to reproduce key structural features and thermodynamics for the CG model, these approaches showed a poor temperature transferability of interaction parameters.¹⁰² Further, these methods do not show chemical transferability and are anticipated to need extra parameterization on a change of the polymer matrix or grafted functional groups or ions.^{11,94} Another limitation of these models is the overestimation of the dynamics of the polymer, which is due to the reduced degrees of freedom in the CG model, which contributes to the substantial decrease in the friction between the CG beads compared to what it would be if the monomers were represented in full atomistic detail. Therefore, the time scales in the CG models do not resemble that of the microscopic chemical system. In addition, these CG models exhibit softer mechanical responses relative to their AA counterpart. While no universally applicable answers to the problems of transferability and representability have been reported, a few strategies have been put forth in the literature. Among them

are the multiscale coarse-graining (MS-CG) approach and the relative entropy method.^{124,125}

In the MS-CG approach, which is an extension of force matching (FM) methods, the variational strategies are used to produce unique, effective CG potentials based on the calculated forces on the particles from atomistic simulation. This process uses an algorithm to minimize the deviations between the atomistic force on a particle calculated from the atomistic simulation and the respective force in the CG counterpart calculated from the CG simulation using a trial CG force field.^{92,126–128} Izvekov, Voth, and co-workers^{126,128} developed a novel multiscale CG method as an early method to determine effective CG potentials. This method derives an optimal CG potential by minimizing a force matching functional of the trial CG force field. The force matching methods have been extensively used in biomolecular systems with considerable success. However, only a few studies have used the FM approach to model polymer–nanoparticle hybrids. For instance, Summers et al.¹²⁹ developed a transferable CG model for amorphous silica nanoparticles with the intent to use it in polymer nanocomposite systems. The CG interaction potentials were derived directly from the AA simulation of nanoparticle models via a simplified version of the potential matching scheme, proposed by Tóth and co-workers¹³⁰ and similar to the force matching approach proposed by Izvekov et al.¹²⁶ They validated the CG parameters by comparing against the target data obtained from the AA simulation of larger nanoparticles, pairs of different sized nanoparticles, and interactions between spherical nanoparticles, dimers, and cross-interaction between nanoparticles and linear alkanes. Further, this CG model was used to investigate the self-assembly of patchy alkane-grafted silica nanoparticles to gain insight into the trends in phase behavior.¹³¹ The results of this study showed that the patchy nanoparticles formed different phases from dispersed to string-like and aggregates. The nanoparticle self-assembling process was dependent on the combination of alkane chain length, grafting density, and fractional grafted surface area.

Recently, different approaches are being implemented to achieve temperature-transferable CG models of polymeric systems, including energy-renormalization,¹³² Bayesian calibration of coarse-grained forces,¹³³ and relative entropy approaches.¹²⁵ For example, Xia et al.¹³² employed the energy-renormalization method for CG parameterization of a polymer. The cohesive interaction strength and effective interaction length-scale parameters were renormalized to modify the activation free energy that occurs upon coarse-graining the dynamics of a polymer. Their model allows the modeling of a polymer over a wide range of temperatures.

Despite the success of these bottom-up approaches, efficiency, accuracy, and transferability of the CG potentials are among the major issues that are typically encountered by the research community. Thus, substantial efforts have been devoted in the past few years to address these issues. Some advanced strategies have been reported to tune the CG potentials for achieving desired outputs. These strategies include systematic local optimization methods (e.g., gradient descent, simplex method, etc.) and metaheuristic methods (e.g., genetic algorithm, particle swarm optimization (PSO), etc.) that are being practiced to fine-tune the CG parameters. The systematic local optimization approaches deploy some general mathematical algorithms to update a scoring function until an optimum set of parameters is achieved. On the other

hand, the metaheuristic methods utilize an educated guess and implement an iterative process to obtain the required solutions. For instance, Lee and Hua¹³⁴ constructed CG interaction parameters for amorphous silica nanoparticles using the simplex optimization approach. The Boltzmann inversion method was implemented to generate the initial guess from the atomistic simulation, and a further penalty function for the RDF was optimized via the simplex method to reproduce the RDF. Recently, a metaheuristic approach, such as the PSO method, has been utilized to develop the transferable CG parameters for water,¹³⁵ cross-linked epoxies,¹³⁶ and amino acids.¹³⁷ However, these approaches are yet to be incorporated in the development of the CG parameters for complex systems such as polymer–nanoparticle hybrid systems.

Among the latest developments, the machine learning approaches have claimed some ground in terms of parameterization of the CG interactions from experimental as well as AA simulation data. McDonagh et al.¹³⁸ proposed a machine learning approach to develop CG parameters for alkane. The Bayesian optimization technique was employed to parameterize CG parameters against experimentally determined partition coefficients. A few studies on multiscale modeling of the polymer–filler interaction have been reported that investigated the interactions between *cis*-1,4-polybutadiene and different solid substrates such as metal oxide (Cu₂O) and silica nanoparticles.^{139–141} The CG interaction parameters of these models were developed using the Bayesian optimization scheme that was based on statistical trajectory matching (STM) of an atomistic description of the system, with the intent to incorporate CG parameters in DPD simulations. However, the preferred choice for a heterogeneous polymer–nanoparticle system among the research community is the Boltzmann inversion process (direct or iterative).

2.2.2. Thermodynamic-Based Coarse-Grained Models. Another popular approach, based on reproduction of energetics, is the MARTINI model.^{85,142} The MARTINI model, a thermodynamics-based CG model, was initially developed to speed up the biomolecular simulations^{85,142–147} and later found a growing number of applications in a diverse field of materials science.^{148–152} The MARTINI coarse-graining approach uses a combination of top-down and bottom-up strategies to determine the CG parameters for different chemical materials (such as lipids,^{153,154} protein,^{155,156} DNA,¹⁵⁷ sugars,^{158,159} polymer,^{78,90,96,100} organic and inorganic nanoparticles,^{31,160,161} etc.) and form an appropriate bridge between atomistic and macroscopic scales. One of the important features that makes the MARTINI model different from the other CG models is its approach. Instead of concentrating on a precise reproduction of the structural properties at a specific state point for a particular system, the MARTINI model targets a wider range of applications without the need to reparameterize the model each time, as is usually observed in the other structure-based CG models like the IBI and DBI approaches. The MARTINI model has been shown to be accurate and up to 200 times faster than the all-atom simulation.⁸⁵ It was shown to capture 75–100% of major collective motions for lipid chains with 5–7-fold faster sampling, albeit it overestimated short-range ordering.¹⁵⁴

The force field parameters (MARTINI FF) in the MARTINI model are designed in a systematic way based on the reproduction of thermodynamic data such as partitioning free energy between an aqueous phase and an organic phase

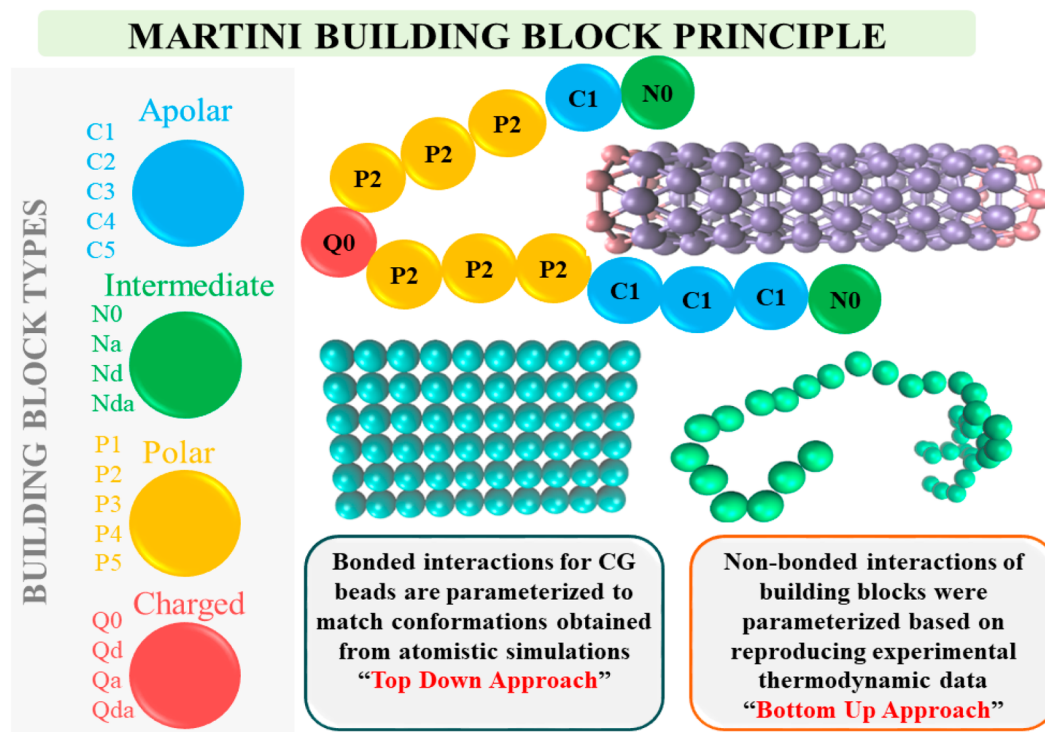


Figure 4. Depiction of MARTINI building block types and CG representations of polymers and nanoparticles.

for a large number of chemical compounds, typically referred to as chemical building blocks (Figure 4).^{85,162} Free energies of transfer of organic compounds typically are used to parameterize the nonbonded interactions between the CG beads. To reproduce the free energies of these chemical building blocks, different types of interaction levels are used to represent the CG beads from a well-designed set of 18 types of interaction sites from the MARTINI model. The interaction levels of these building blocks were determined after an extensive calibration against the thermodynamic data, in particular oil/water partitioning coefficients.^{85,142,163} A similar approach has been used to develop an all-atom GROMOS force field. In addition, the effective CG bonded parameters were developed by using a bottom-up approach, which includes the matching targeted distribution of bonded terms (bond length, angle, and dihedral) obtained from the atomistic simulation data.^{79,147}

In the MARTINI model, a CG bead or chemical building block is composed of 3–4 heavy atoms with their linked hydrogen atoms. This mapping scheme effectively decreases the number of particles to be simulated in a system and helps to improve the simulation speed significantly. In addition, the smoother CG energy landscape leads to faster overall dynamics and allows the use of larger time steps compared to all-atom simulations. The MARTINI beads are classified into four main types on the basis of their polarity, namely, polar (P), nonpolar (N), apolar (C), and charged (Q). These are further categorized into subtypes on the basis of either polarity (ranging from 1 = low polarity to 5 = high polarity) or their hydrogen-bonding capabilities (donor, acceptor, both, or none). Thus, this gives a total of 18 unique MARTINI building blocks. Such a building-block strategy offers a relatively straightforward and systematic framework for switching from atomistic to CG model for an extensive range of biological, polymeric, and soft material systems. Further, a limited number of interaction levels between distinct types of

particles facilitate easy parameterization of new molecules, albeit limiting the quantitative accuracy of the force field.

In light of the underlying chemical building block principle of the MARTINI model, it is quite possible to model a variety of multicomponent systems. The MARTINI model enjoyed a remarkable success for modeling of a variety of biomolecular processes and has been incorporated by the worldwide user community to study a large number of systems including lipid membrane, protein, sugar, DNA, RNA, hydrocarbons, short peptides, polymers, etc.^{78,79,143–145,148–153,155–159} In the past decade, the MARTINI model has been used successfully to simulate a variety of polymeric systems including homogeneous polymers, e.g., polyethylene (PE), polypropylene (PP),⁷⁸ polyethylene glycol (PEO),¹⁰⁰ and polystyrene (PS).⁷⁹ MARTINI CG parameters (bonded and nonbonded) for polymers typically are constructed by matching bond and angle distributions obtained from reference all-atom simulations, the free energy of transfer of the target repeating units in organic and aqueous phases, and long-range structural properties such as radii of gyration.^{78,79,164} Apart from that, polymer melt density profile, structure factor, end-to-end distance, and persistence length can also be used as the validation target. Currently, the MARTINI CG parameters are available for >50 types of polymers ranging from simple linear and branched polymers to conjugate polymers such as poly(3-hexylthiophene) and block copolymers.^{78,79,90,149,164–166} More recently, it has been successfully used to simulate a variety of organic–inorganic systems such as block copolymers assembly,⁹⁰ organic–electronic materials,^{167,168} ionic liquids,¹⁴⁸ ion-conducting materials,^{169–171} polymer nanocomposites, self-assembled supramolecular materials,^{172,173} and many others.^{152,174} In the past decade, the MARTINI models have also been used for more complex polymer–nanoparticle systems such as graphene, carbon nanotubes, gold, and montmorillonite clay nanoparticle–polymer composites and

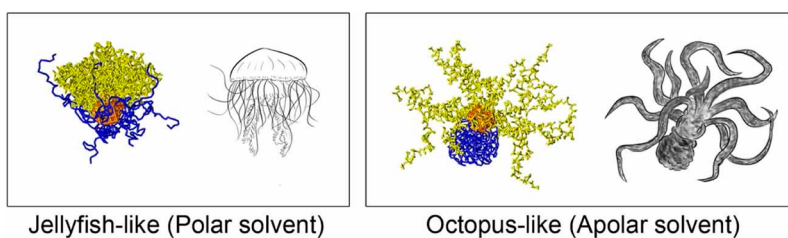


Figure 5. Depiction of jellyfish-like and octopus-like morphologies of AuNP-JANUS. Reprinted with permission from ref 179. Copyright 2013 John Wiley and Sons.

polymers near graphite and silica surfaces. There are various studies that involve the interaction of these nanoparticles with biomolecules and polymers conducted using the MARTINI CG parameters, of which a few studies related to PNCs and polymer-tethered nanoparticles are discussed here.

For example, the MARTINI CG parameters have been developed for carbon-based nanoparticles such as carbon nanotube (CNT), graphene, graphite, etc. and frequently used to study the interaction between nanoparticles and biomolecules. The MARTINI model was also used to investigate the mechanism of adsorption of detergents onto a carbon nanotube.¹⁷⁵ Additionally, the MARTINI CG parameters were used to explore the interaction between CNT and polymer recently. For example, the conformational behavior of a polyethylene glycol (PEG) polymer attached covalently and noncovalently to the CNT has been investigated in a detailed way in various studies. Lee performed a CG molecular simulation of a single-wall CNT with different lengths and densities of polyethylene glycol polymer.^{164,176} The PEGs were either covalently grafted or noncovalently self-assembled to the SWNT. They established the correlation for diffusivities and conformations of SWNT-PEG complexes with the PEG length and grafting density and successfully reproduced the experimentally proposed conformation of PEGs on SWNTs. They also showed the mushroom-to-brush transition of PEG chains, which was in good accordance with the Alexander-de Gennes theory. Furthermore, the MARTINI parameters were also used to understand the selective molecular recognition of different categories of analytes by the SWCNT-PEG-based polymer sensors. This study might be helpful to screen and select polymers candidates while designing the molecular recognition sensors.¹⁷⁷ Another example of a carbon nanoparticle-based polymer nanocomposite is graphite-filled polymer composites. Recently, the MARTINI model was used to understand the preferential adsorption of long-chain organic molecules on the graphite surface from the solvent and the formation of ordered structures on the surface through self-assembly.¹⁶¹ In another study, Shi et al. performed a CG-MD simulation using the MARTINI parameters to understand the change in mechanical and dielectric properties and crystalline behavior of the graphite-filled polyethylene polymer composites and compare with the findings obtained from experimental study. The microstructural evolution of the composites during lamination was also explored with MD simulations.¹⁷⁸

In addition to the carbon-based nanoparticle-polymer hybrid systems, the MARTINI framework also has been used to construct the CG parameters of inorganic nanoparticles such as gold, silica, and clay. For example, the CG parameters were developed for the polymer-grafted gold nanoparticles and used to investigate the solvent-responsive behavior of grafted

nanoparticles and structural properties of polymer grafted onto gold nanoparticles. Dong and Zhou performed the CG simulation of PS-*b*-PEO block copolymer-grafted gold nanoparticles dissolved in different solvents of different polarities using the MARTINI CG parameters.^{179,180} Different compositions of PS-*b*-PEO block copolymer, grafting densities, chain lengths, asymmetries of nanoparticles, and variations in solvent polarity were used to investigate the solvent-responsive behavior of amphiphilic polymer brush grafted onto nanoparticles. They observed core-shell, Janus-type, buckle, ring, jellyfish-like, and octopus-like morphologies of nanoparticles as a consequence of block sequence and mixing methods (Figure 5). Further, the MARTINI model was used to examine the interfacial behaviors of polymer-grafted gold nanoparticles with various grafting architectures at the oil-water interface.⁸⁷ These studies can be useful to design polymer-grafted nanoparticles for specific applications. Recently, Dahal and co-workers described the solvation phenomenon of polymer-grafted gold nanoparticles in water through a CG-MD simulation, which remains a challenge experimentally. Their results showed that the hydration process depends on the polymer grafting density and radius of curvature of the nanoparticles and were in agreement with experimental data.¹⁸¹ Dahal and Dormidontova further investigated the chain conformation and hydration of PEO-grafted gold nanoparticles as a function of polymer chain length and grafting density.¹⁸²

Recently, Perrin et al.¹⁸³ used the MARTINI CG model to study the conformations and dynamics of solvated polymers near the silica nanoparticle surface. They used poly-(diallyldimethylammonium) (PDMA) and poly(acrylamide) (PAAm) polymers to study the effect of differences in the nature of the polymer and the polymer-solvent interactions on the behavior of the polymer-surface adhesion. The results of this study showed that the PDMA preferably adsorbed on the silica surface, whereas PAAm was well-solvated by water and preferred to be surrounded by solvent beads rather than close to silica beads.

More recently, Khan and Goel developed the MARTINI CG parameters for polymer clay heterogeneous systems to investigate the role of clay particles on structural, dynamic, and thermodynamic properties of a polymer melt. In this work, they used an alternative approach to construct the bonded and nonbonded parameters that are compatible with the existing MARTINI force field (MARTINI FF) for polymer clay nanocomposite systems.³¹ The nonbonded interaction parameters were parameterized from the cleavage energy of organically modified montmorillonite (oMMT) clay particles, whereas the mechanical properties such as Young's modulus of clay particles were used to parameterize the bonded interaction parameters. The parameters of the bonded interactions were

tuned so as to reproduce the distributions of bonds and angles obtained from all-atom simulations, in the same fashion as for other MARTINI polymers. To fine-tune the nonbonded interaction parameters, individual dispersive and polar contributions to oMMT cleavage energy were used to determine the appropriate MARTINI bead types for the CG model of oMMT clay. The surface energy is determined by allowing for full surface reconstruction corresponding to a slow equilibrium cleavage process.¹⁸⁴ To ensure the transferability of developed parameters, different types of polymer (PP, PE, or PS) and temperatures were used to simulate the polymer–clay system. This model accurately reproduces the structural, thermodynamic, and dynamic properties of a polymer–clay system.

The previous discussion suggests that CG simulation of a polymer–nanoparticle system using interaction parameters developed from the IBI or DBI technique predicted significantly higher dynamics (8–20 times that of the AA model) of polymer chains in nanocomposites.^{11,185,67} Structure-based models (IBI and IDI techniques) predicted structure very well but sometimes failed to deliver correct dynamics. It was also reported that a number of different sets of all-atom simulations were required for each polymer–particle system to generate CG parameters.^{67,11} Inversely, in the case of the MARTINI model, only one atomistic simulation is required to develop interaction parameters, and the same parameters can be used while working with other polymers. Despite the enormous success of top-down approaches such as the MARTINI model, the main limitation encountered in the use of these models is the need for reliable experimental data to be used as a reference. However, in most of the cases for which it is of practical interest to develop a CG model, experimental results are often not available. Therefore, the approach to construct CG interaction parameters from experimental data becomes increasingly difficult with an increasing number of distinct representative pseudoatom types in a CG model. However, widespread use of the MARTINI model helped to identify its limitations.^{142,186} This gave the direction for the development of a new version called MARTINI 3, which enables more accurate simulation of biomolecules, polymers, and many others.¹⁶³ MARTINI 3 employed a more generalized approach (such as free energies of transfer and miscibility data on binary mixtures) to parameterize the CG interactions, which will further promote its application in polymer science.¹⁶³ However, issues of temperature transferability^{187,188} and representability^{188,189} are still part of the new model, as observed in some studies.^{163,186,188,189}

3. DISCUSSION AND CONCLUSION

Here, we have reviewed the progress and challenges in the field of CG molecular simulations of polymer–nanoparticle hybrid systems in a detailed and results-driven manner. The successful development of these organic–inorganic hybrid materials requires a broad understanding of the phenomena at different time and length scales (ranging from molecular scale to macroscale). The methodologies utilizing multiscale molecular modeling and simulation methods have proven to be valuable toward investigating the complex phenomena transpiring during the formation of polymer–particle hybrids, something which experiments alone cannot fully achieve. The study of organic–inorganic hybrid materials using multiscale simulation is a very popular research area that attempts to address the

issues related to the following topics: (1) the deviation in the polymer properties (e.g., structural, dynamic, mechanical, physical, and thermodynamic), due to the presence of nanoparticles, from their bulk values; (2) the extent of increment or reduction in properties from the solid surface; (3) the need to deliver a better understanding of the mechanism of nanoparticle exfoliation or dispersion in the polymer matrix; (4) the changes in phase boundaries and phase behavior; and (5) the thermodynamic stability of the hybrid system. Due to the time and length constraints observed in the AA simulations, many successful CG models have been developed using the atomistic simulation data to address these issues.

Within the context of the CG simulation perspective, various approaches for modeling processes occurring in the formation of nanoparticle hybrid systems can be classified into two major categories, namely, generic and chemically specific approaches. The chemically specific approach is further categorized into two major categories, namely, structure-based and thermodynamics-based approaches. This classification lends itself to an easy examination of these methodologies and the complex systems to which they are applied.

We note that the characterization of the polymer behavior near the surface is more challenging as compared to the bulk polymers, because the structure of polymers near the surface relies upon the intermolecular interactions and the geometry of the surface. Thus, it is very sensitive to the chemical structure of the confined nanoparticles, and a limited number of reports on chemically specific CG models for polymer clay nanocomposites are available. However, a lot of the work involves the use of simple bead–spring models that are CG models with little chemical details that have used a bead–spring model of a polymer near structure-less surfaces.^{48,72} Later, extensive work was done to include more information on the structure and nature of interactions between polymer and particles.^{81,82,103–106} This chemically specific approach involves the use of IBI, DBI, force matching, and MARTINI methods to obtain the CG interaction parameters for the systems with more details of particle structure and particle–polymer, particle–particle, and polymer–polymer interactions. The CG models allow a substantial alleviation of both the spatial and temporal limitations of all-atom models by averaging out some of the atomistic degrees of freedom. It performs better on reproducing the structural and thermodynamic properties. Finally, the CG models have allowed the extension of the realm of molecular dynamics simulations to the mesoscale, with comparative predictive performance in terms of dynamic, structural, thermodynamic, and mechanical properties.

Despite a number of improvements in the CG models of polymer–nanoparticle hybrid materials to address the aforementioned issues, there are still many open issues and challenges in terms of fundamental physics and the development of approaches taken toward the simulations. In this article, we have accounted for all such open challenges that are still believed to be among the important and relevant questions. Further, the issues like glass transition temperature, chain dynamics, prediction of thermodynamic properties, geometric effects, fluctuation at interface, etc. need to be addressed carefully while working with the CG models. Presently, the CG modeling requires careful consideration toward the coarseness of the system, underlying energy functions, and sampling scheme being employed. These

parameters must be fine-tuned to address a specific query in a specific model under investigation.

One of the key challenges encountered in the molecular simulations of polymer–nanoparticle hybrid systems is the development of highly heterogeneous systems (e.g., nanoclay in polymer matrix) having many nanoparticles. This may allow the study of collective phenomena related to the effective interactions between nanoparticles at the molecular level, as a function of the distance between them and corresponding concentrations. This is principally significant if it is considered that experimentally the solubility or exfoliation of nanoparticles is a quite problematic issue. Furthermore, the focus should be toward the development of systematic methodologies to connect techniques over a wider range of length and time scales. However, a major issue encountered in the development of CG potentials for these systems is the requirement of AA reference distributions, which have been found to be difficult for anisotropic structures due to the convergence issues. Further, the derived potentials for nanoparticles might lack transferability to other systems, although the AA simulations are quite successful to address the changes in morphology and phase behavior, but at short time and length scales. Therefore, to connect the CG simulations with all-atom simulations, a precise estimation of the CG bead–surface effective free energy calculated through nonbonded potential and correct incorporation of the local conformation and rigidity of the polymer chain in the CG model are imperative. Further, the CG models help the extension of multiscale molecular simulation studies to the mesoscale. Therefore, it is necessary to extend and/or develop some new CG methodologies that can accurately reproduce structural and thermodynamic characteristics of the heterogeneous polymer hybrid system to address morphological changes.

Furthermore, despite the enormous success to reproduce key structural features, the quantitative prediction of dynamics of polymer–solid systems via simulation methodologies is a critical issue for the structure-based approaches. The averaging over atomic degrees of freedom may potentially reduce the activation barriers that are present in the potential landscape of the CG model and could lead to more diffusive movement through the configuration space. The elimination of explicit atomic interactions that are responsible to generate friction against motion could result in a relatively less viscous environment in CG models, which in turn accelerates its dynamic processes and sampling. The statistical models and theories suggested that the reduced degrees of freedom are associated with configurational entropy, while coarse-graining causes a significant reduction in fluctuations and fractional forces associated with atomistic details, which further leads to the faster dynamics in CG models. However, these effects also pose substantial challenges toward interpreting the CG dynamics because not all of the processes in the CG model are necessarily accelerated to the same degree. The net result of these considerations leads to the 3 or more orders of magnitude efficiency of CG models compared to the atomistic models. This enables simulations of systems and phenomena that could not otherwise be investigated, allows for quantitative comparisons with experimental observations, and also provides the efficiency required for achieving adequate convergence of free energies and dynamic quantities. To correctly determine the dynamic and transport properties using the CG models, a typical approach is to scale down or scale up the CG time scale in bulk systems based on either a postprocessing time rescaling

step or the inclusion of friction forces in the equations of motion. The CG schemes for reproducing the dynamic and transport properties are yet to be explored completely to achieve the state-of-the-art for delivering the desired outcomes. Therefore, it is necessary to extend and/or develop new methodologies to overcome this issue.

The equilibration issues are very critical in modeling highly heterogeneous polymer–nanoparticle systems having long polymeric chains. The equilibration time for high molecular weight chains with entanglement is sufficiently high. Further, it is observed that the dynamics of polymer chains near the solid surface become slower, requiring more computational time to equilibrate the system. Therefore, CG simulations are proving greatly helpful to address the equilibration issue. The CG approaches can be used to generate the equilibrium morphologies for further analysis through atomistic simulations after back-mapping the CG structure to the AA structure. The back-mapping process in the CG simulation of polymer nanocomposites is useful in bypassing long or untenable equilibration times, which can be caused due to slow diffusion and relaxation of entangled polymer chains. Further, for specific multiscale simulation paradigms or when features of atomistic details are required, back-mapping processes are quite useful to reintroduce lost degrees of freedom.

Further, another major issue that arises with the coarse-graining procedure is the question of transferability of the final CG model. The CG models generally encountered temperature/thermodynamic and chemical transferability issues. The temperature transferability issue arises because most of the bottom-up approaches calibrated CG potentials to reproduce targeted properties at or near the specified thermodynamic state, so developed potentials often fail to accurately predict the same properties at different thermodynamic states. Temperature transferability might be a big issue for the determination of glass transition temperature and mechanical properties of polymer nanocomposites. To determine these properties, polymeric systems need to simulate over a wide range of temperatures from high to well below the glass transition temperature. Therefore, if the CG potentials are not temperature-transferable, then they will not accurately predict these properties. However, recently some new methodologies have been proposed to overcome this issue. For instance, the multiscale IBI, relative entropy framework, energy renormalization, etc. approaches have shown remarkable temperature transferability for homogeneous systems, although these methods need to be tested for multicomponent heterogeneous systems such as polymer nanocomposites. Another subtle issue is the chemical transferability, which arises due to the inability of the developed CG parameters to work with different chemical species. The CG potentials are the effective potentials that furnish partially limited transferability, as revealed by the requirement for additional parameterization when modeling the same polymer with different nanoparticles or environments. To reproduce the distribution observed in atomistic simulations, the many-body PMF is typically approximated with simple potentials, e.g., nonbonded pair potentials are optimized to reproduce the corresponding pair distribution functions. These pair distribution functions may work well with liquids, pure melt, etc. but are not efficient enough to construct effective CG potentials to work with more complex or heterogeneous systems. As a result of coarse-graining over atomic degrees of freedom, many physical details of the system are lost. Because these features may vary from system to

system and may have varying importance with changes in the thermodynamic state, an effective potential that provides a reasonable description for modeling, one particular system or thermodynamic state may not be transferable or may not provide adequate desired accuracy for modeling the same system with a different environment. Investigation of transferability conditions could help to gain insight into fundamental principles that govern the behavior of the system. It is anticipated that the emergence of new CG models in terms of better transferability will help to extend its applicability to the study of new phenomena at large length and longer time scales. To ensure the wide range of transferability of the CG potentials, the main focus should be on the development of a general approach to construct interaction potentials. The challenges discussed here are just a few examples among many other challenges, such as model assessment, integration of multiple CG models, and adaptive resolution.

It is fairly clear from this review that the different multiscale approaches have furnished precious insights into the structure, dynamics, and thermodynamics of polymeric hybrid materials. However, the new CG schemes with fair degrees of temperature and chemical transferability along with the capability of reproducing the dynamic and transport properties are yet to be explored completely to achieve the state-of-the-art for delivering the desired outcomes; hence, numerous research studies are in progress in this area. In general, unique insights available through the simulation of materials at a range of scales (quantum \rightarrow molecular \rightarrow mesoscale) can generate a lot of insight into the system, significantly decrease experimental efforts, allow optimization of processes, and permit screening of large numbers of candidate materials prior to the production. Therefore, a multiscale computational approach that allows accurate representation of each length and time scale can play an essential role in designing and predicting polymeric materials with target properties.¹⁹ Despite all the studies discussed here, there is still a need for a thorough, systematic, and comprehensive investigation to deal with the multiscale modeling and simulations of polymer nanocomposites covering all length scales, with an aim to study the morphology phenomena and the prediction of macroscopic effective properties.

In a nutshell, the development of hierarchical or multiscale molecular modeling methods for highly heterogeneous systems is an interesting field in the computer-aided simulation of soft matters, with a major objective of direct quantitative comparison of properties calculated from experiments and simulations. To attain this, new mathematical and computational approaches are required. Insights obtained from this review will not only stimulate the field to rationally design polymer–nanoparticle hybrid materials with excellent properties but also foster research to predict structure–property relationships of hybrid materials at the molecular level.

AUTHOR INFORMATION

Corresponding Author

Parvez Khan – Department of Chemical Engineering, Aligarh Muslim University, Aligarh 202002, India; orcid.org/0000-0003-0865-145X; Email: pkhan@myamu.ac.in

Authors

Rahul Kaushik – Laboratory for Structural Bioinformatics, Center for Biosystems Dynamics Research, RIKEN,

Yokohama, Kanagawa 230-0045, Japan; Present Address: Biotechnology Research Center, Technology Innovation Institute, P.O. Box 9639, Masdar City, Abu Dhabi, UAE

Abhilash Jayaraj – Department of Chemistry, Wesleyan University, Middletown, Connecticut 06459, United States

Complete contact information is available at:

<https://pubs.acs.org/10.1021/acsomega.2c06248>

Author Contributions

The main idea and outline of the manuscript was conceived by P.K. P.K. wrote the chemically specific coarse-grained model section and conclusion. P.K., R.K., and A.J. contributed to the initial draft and preparation of the figures and to the generic CG model details. All of the authors read and approved the manuscript.

Notes

The authors declare no competing financial interest.

REFERENCES

- (1) Yang, L.; Zhang, L.; Webster, T. J. Nanobiomaterials: State of the Art and Future Trends. *Adv. Eng. Mater.* **2011**, *13* (6), B197–B217.
- (2) Grumezescu, A.; Holban, A. *Impact of Nanoscience in the Food Industry*; Elsevier: 2018; DOI: [10.1016/c2016-0-00498-9](https://doi.org/10.1016/c2016-0-00498-9).
- (3) Jaafar, M. Development of Hybrid Fillers/Polymer Nanocomposites for Electronic Applications. *Hybrid Nanomaterials* **2017**, 349–369.
- (4) Deng, J.; Ding, X.; Zhang, W.; Peng, Y.; Wang, J.; Long, X.; Li, P.; Chan, A. S. C. Carbon Nanotube-Polyaniline Hybrid Materials. *Eur. Polym. J.* **2002**, *38* (12), 2497–2501.
- (5) Oueiny, C.; Berlioz, S.; Perrin, F. X. Carbon Nanotube-Polyaniline Composites. *Prog. Polym. Sci.* **2014**, *39* (4), 707–748.
- (6) Camargo, P. H. C.; Satyanarayana, K. G.; Wypych, F. Nanocomposites: Synthesis, Structure, Properties and New Application Opportunities. *Mater. Res.* **2009**, *12* (1), 1–39.
- (7) Sorrentino, A.; Gorrasi, G.; Vittoria, V. Potential Perspectives of Bio-Nanocomposites for Food Packaging Applications. *Trends Food Sci. Technol.* **2007**, *18* (2), 84–95.
- (8) Garcés, J. M.; Moll, D. J.; Bicerano, J.; Fibiger, R.; McLeod, D. G. Polymeric Nanocomposites for Automotive Applications. *Adv. Mater.* **2000**, *12* (23), 1835–1839.
- (9) Sanchez, C.; Julián, B.; Belleville, P.; Popall, M. Applications of Hybrid Organic-Inorganic Nanocomposites. *J. Mater. Chem.* **2005**, *15* (35–36), 3559–3592.
- (10) Hule, R. A.; Pochan, D. J. Polymer Nanocomposites for Biomedical Applications. *MRS Bull.* **2007**, *32* (4), 354–358.
- (11) Suter, J. L.; Groen, D.; Coveney, P. V. Chemically Specific Multiscale Modeling of Clay-Polymer Nanocomposites Reveals Intercalation Dynamics, Tactoid Self-Assembly and Emergent Materials Properties. *Adv. Mater.* **2015**, *27* (6), 966–984.
- (12) Pereira, S. P.; Scocchi, G.; Toth, R.; Posocco, P.; Nieto, D. R.; Priel, S.; Fermeglia, M. Multiscale Modeling of Polymer/Clay Nanocomposites. *J. Multiscale Model.* **2011**, *03* (03), 151–176.
- (13) Dunkerley, E.; Koerner, H.; Vaia, R. A.; Schmidt, D. Structure and Dynamic Mechanical Properties of Highly Oriented PS/Clay Nanolaminates over the Entire Composition Range. *Polymer (Guildf)* **2011**, *52* (4), 1163–1171.
- (14) Dunkerley, E.; Schmidt, D. Effects of Composition, Orientation and Temperature on the O₂ Permeability of Model Polymer/Clay Nanocomposites. *Macromolecules* **2010**, *43* (24), 10536–10544.
- (15) Picard, E.; Gérard, J.-F.; Espuche, E. Reinforcement of the Gas Barrier Properties of Polyethylene and Polyamide Through the Nanocomposite Approach: Key Factors and Limitations. *Oil Gas Sci. Technol. - Rev. IFP Energies Nouv.* **2015**, *70* (2), 237–249.

- (16) Picard, E.; Vermogen, A.; Gérard, J. F.; Espuche, E. Barrier Properties of Nylon 6-Montmorillonite Nanocomposite Membranes Prepared by Melt Blending: Influence of the Clay Content and Dispersion State. Consequences on Modelling. *J. Membr. Sci.* **2007**, *292* (1–2), 133–144.
- (17) Durmuş, A.; Woo, M.; Kaşgöz, A.; Macosko, C. W.; Tsapatsis, M. Intercalated Linear Low Density Polyethylene (LLDPE)/Clay Nanocomposites Prepared with Oxidized Polyethylene as a New Type Compatibilizer: Structural, Mechanical and Barrier Properties. *Eur. Polym. J.* **2007**, *43* (9), 3737–3749.
- (18) Pavlidou, S.; Papaspyrides, C. D. A Review on Polymer-Layered Silicate Nanocomposites. *Prog. Polym. Sci.* **2008**, *33* (12), 1119–1198.
- (19) Zeng, Q. H.; Yu, A. B.; Lu, G. Q. Multiscale Modeling and Simulation of Polymer Nanocomposites. *Prog. Polym. Sci.* **2008**, *33* (2), 191–269.
- (20) Sheng, N.; Boyce, M. C.; Parks, D. M.; Rutledge, G. C.; Abes, J. I.; Cohen, R. E. Multiscale Micromechanical Modeling of Polymer/Clay Nanocomposites and the Effective Clay Particle. *Polymer (Guildf)* **2004**, *45* (2), 487–506.
- (21) Vaia, R. A.; Giannelis, E. P. Lattice Model of Polymer Melt Intercalation in Organically-Modified Layered Silicates. *Macromolecules* **1997**, *30* (25), 7990–7999.
- (22) Balazs, A. C.; Singh, C.; Zhulina, E. Modeling the Interactions between Polymers and Clay Surfaces through Self-Consistent Field Theory. *Macromolecules* **1998**, *31* (23), 8370–8381.
- (23) Greathouse, J.; Johnson, K.; Greenwell, H. Interaction of Natural Organic Matter with Layered Minerals: Recent Developments in Computational Methods at the Nanoscale. *Minerals* **2014**, *4* (2), 519–540.
- (24) Ginzburg, V. V.; Singh, C.; Balazs, A. C. Theoretical Phase Diagrams of Polymerclay Composites: The Role of Grafted Organic Modifiers. *Macromolecules* **2000**, *33* (3), 1089–1099.
- (25) Buxton, G. A.; Balazs, A. C. Lattice Spring Model of Filled Polymers and Nanocomposites. *J. Chem. Phys.* **2002**, *117* (16), 7649–7658.
- (26) Ginzburg, V. V.; Balazs, A. C. Calculating Phase Diagrams of Polymer-Platelet Mixtures Using Density Functional Theory: Implications for Polymer/Clay Composites. *Macromolecules* **1999**, *32* (17), 5681–5688.
- (27) Ginzburg, V. V.; Weinhold, J. D.; Jog, P. K.; Srivastava, R. Thermodynamics of Polymer-Clay Nanocomposites Revisited: Compressible Self-Consistent Field Theory Modeling of Melt-Intercalated Organoclays. *Macromolecules* **2009**, *42* (22), 9089–9095.
- (28) Ganesan, V.; Jayaraman, A. Theory and Simulation Studies of Effective Interactions, Phase Behavior and Morphology in Polymer Nanocomposites. *Soft Matter* **2014**, *10* (1), 13–38.
- (29) Jain, A.; Sunthar, P.; Dünweg, B.; Prakash, J. R. Optimization of a Brownian-Dynamics Algorithm for Semidilute Polymer Solutions. *Phys. Rev. E - Stat. Nonlinear, Soft Matter Phys.* **2012**, *85* (6), 066703.
- (30) Groot, R. D.; Warren, P. B. Dissipative Particle Dynamics: Bridging the Gap between Atomistic and Mesoscopic Simulation. *J. Chem. Phys.* **1997**, *107* (11), 4423.
- (31) Khan, P.; Goel, G. Martini Coarse-Grained Model for Clay-Polymer Nanocomposites. *J. Phys. Chem. B* **2019**, *123* (42), 9011–9023.
- (32) Suter, J. L.; Groen, D.; Coveney, P. V. Mechanism of Exfoliation and Prediction of Materials Properties of Clay-Polymer Nanocomposites from Multiscale Modeling. *Nano Lett.* **2015**, *15* (12), 8108–8113.
- (33) Grest, G. S. *Resolving Properties of Polymers and Nanoparticle Assembly through Coarse-Grained Computational Studies*; U.S. Department of Energy: 2017; DOI: 10.2172/1395439.
- (34) Johnson, L. C.; Phelan, F. R. Dynamically Consistent Coarse-Grain Simulation Model of Chemically Specific Polymer Melts via Friction Parameterization. *J. Chem. Phys.* **2021**, *154* (8), 084114.
- (35) Kuppa, V.; Menakanit, S.; Krishnamoorti, R.; Manias, E. Simulation Insights on the Structure of Nanoscopically Confined Poly(Ethylene Oxide). *J. Polym. Sci., Part B: Polym. Phys.* **2003**, *41* (24), 3285–3298.
- (36) Sinsawat, A.; Anderson, K. L.; Vaia, R. a.; Farmer, B. L. Influence of Polymer Matrix Composition and Architecture on Polymer Nanocomposite Formation: Coarse-Grained Molecular Dynamics Simulation. *J. Polym. Sci., Part B: Polym. Phys.* **2003**, *41* (24), 3272–3284.
- (37) Johnston, K.; Harmandaris, V. Hierarchical Simulations of Hybrid Polymer–Solid Materials. *Soft Matter* **2013**, *9* (29), 6696–6710.
- (38) Ruzinski, J. F. Recent Progress towards Chemically-Specific Coarse-Grained Simulation Models with Consistent Dynamical Properties. *Comput. 2019, Vol. 7, Page 42* **2019**, *7* (3), 42.
- (39) Brini, E.; Algaer, E. A.; Ganguly, P.; Li, C.; Rodríguez-Ropero, F.; Van Der Vegt, N. F. A. Systematic Coarse-Graining Methods for Soft Matter Simulations – a Review. *Soft Matter* **2013**, *9* (7), 2108–2119.
- (40) Kmieciak, S.; Gront, D.; Kolinski, M.; Wieteska, L.; Dawid, A. E.; Kolinski, A. Coarse-Grained Protein Models and Their Applications. *Chem. Rev.* **2016**, *116* (14), 7898–7936.
- (41) de Pablo, J. J. Coarse-Grained Simulations of Macromolecules: From DNA to Nanocomposites. *Annu. Rev. Phys. Chem.* **2011**, *62*, 555–574.
- (42) Peter, C.; Kremer, K. Multiscale Simulation of Soft Matter Systems – from the Atomistic to the Coarse-Grained Level and Back. *Soft Matter* **2009**, *5* (22), 4357–4366.
- (43) Noid, W. G. Perspective: Coarse-Grained Models for Biomolecular Systems. *J. Chem. Phys.* **2013**, *139* (9), 090901.
- (44) Dhamankar, S.; Webb, M. A. Chemically Specific Coarse-Graining of Polymers: Methods and Prospects. *J. Polym. Sci.* **2021**, *59* (22), 2613–2643.
- (45) Hagita, K.; Morita, H.; Doi, M.; Takano, H. Coarse-Grained Molecular Dynamics Simulation of Filled Polymer Nanocomposites under Uniaxial Elongation. *Macromolecules* **2016**, *49* (5), 1972–1983.
- (46) De Virgiliis, A.; Milchev, A.; Rostiasvili, V. G.; Vilgis, T. A. Structure and Dynamics of a Polymer Melt at an Attractive Surface. *Eur. Phys. J. E. Soft Matter* **2012**, *35* (9), 97.
- (47) Rüttgers, A.; Griebel, M. Multiscale Simulation of Polymeric Fluids Using the Sparse Grid Combination Technique. *Appl. Math. Comput.* **2018**, *319*, 425–443.
- (48) Bitsanis, I.; Hadziioannou, G. Molecular Dynamics Simulations of the Structure and Dynamics of Confined Polymer Melts. *J. Chem. Phys.* **1990**, *92*, 3827–3847.
- (49) Matsuda, T.; Smith, G. D.; Winkler, R. G.; Yoon, D. Y. Stochastic Dynamics Simulations of N-Alkane Melts Confined between Solid Surfaces: Influence of Surface Properties and Comparison with Scheutjens-Fleer Theory. *Macromolecules* **1995**, *28* (1), 165–173.
- (50) Aoyagi, T.; Takimoto, J. I.; Doi, M. Molecular Dynamics Study of Polymer Melt Confined between Walls. *J. Chem. Phys.* **2001**, *115* (1), 552–559.
- (51) Mansfield, K. F.; Theodorou, D. N. Interfacial Structure and Dynamics of Macromolecular Liquids: A Monte Carlo Simulation Approach. *Macromolecules* **1989**, *22*, 3143–3152.
- (52) Klos, J.; Pakula, T. Interaction of a Spherical Particle with Linear Chains. *J. Chem. Phys.* **2003**, *118* (3), 1507.
- (53) Grest, G. S. Grafted Polymer Brushes in Polymeric Matrices. *J. Chem. Phys.* **1996**, *105* (13), 5532.
- (54) Klos, J.; Pakula, T. Computer Simulations of Chains End-Grafted onto a Spherical Surface. Effect of Matrix Polymer. *Macromolecules* **2004**, *37* (21), 8145–8151.
- (55) Kalb, J.; Dukes, D.; Kumar, S. K.; Hoy, R. S.; Grest, G. S. End Grafted Polymer Nanoparticles in a Polymeric Matrix: Effect of Coverage and Curvature. *Soft Matter* **2011**, *7* (4), 1418–1425.
- (56) Smith, G. D.; Bedrov, D.; Li, L.; Bytner, O. A Molecular Dynamics Simulation Study of the Viscoelastic Properties of Polymer Nanocomposites. *J. Chem. Phys.* **2002**, *117* (20), 9478.
- (57) Starr, F. W.; Douglas, J. F.; Glotzer, S. C. Origin of Particle Clustering in a Simulated Polymer Nanocomposite and Its Impact on Rheology. *J. Chem. Phys.* **2003**, *119* (3), 1777.

- (58) Shen, J.; Liu, J.; Li, H.; Gao, Y.; Li, X.; Wu, Y.; Zhang, L. Molecular Dynamics Simulations of the Structural, Mechanical and Visco-Elastic Properties of Polymer Nanocomposites Filled with Grafted Nanoparticles. *Phys. Chem. Chem. Phys.* **2015**, *17* (11), 7196–7207.
- (59) Lipson, J. E. G.; Milner, S. T. Percolation Model of Interfacial Effects in Polymeric Glasses. *Eur. Phys. J. B* **2009**, *72* (1), 133–137.
- (60) Kropka, J. M.; Pryamitsyn, V.; Ganesan, V. Relation between Glass Transition Temperatures in Polymer Nanocomposites and Polymer Thin Films. *Phys. Rev. Lett.* **2008**, *101* (7), 075702.
- (61) Kropka, J. M.; Putz, K. W.; Pryamitsyn, V.; Ganesan, V.; Green, P. F. Origin of Dynamical Properties in PMMA–C60 Nanocomposites. *Macromolecules* **2007**, *40* (15), 5424–5432.
- (62) Karatrantos, A.; Composto, R. J.; Winey, K. I.; Kröger, M.; Clarke, N. Entanglements and Dynamics of Polymer Melts near a SWCNT. *Macromolecules* **2012**, *45* (17), 7274–7281.
- (63) Chakrabarti, R.; Schweizer, K. S. Polymer-Mediated Spatial Organization of Nanoparticles in Dense Melts: Transferability and an Effective One-Component Approach. *J. Chem. Phys.* **2010**, *133* (14), 144905.
- (64) Hooper, J. B.; Schweizer, K. S. Theory of Phase Separation in Polymer Nanocomposites. *Macromolecules* **2006**, *39* (15), 5133–5142.
- (65) Yamamoto, U.; Schweizer, K. S. Theory of Nanoparticle Diffusion in Unentangled and Entangled Polymer Melts. *J. Chem. Phys.* **2011**, *135* (22), 224902.
- (66) Hall, L. M.; Jayaraman, A.; Schweizer, K. S. Molecular Theories of Polymer Nanocomposites. *Curr. Opin. Solid State Mater. Sci.* **2010**, *14* (2), 38–48.
- (67) Volgin, I. V.; Larin, S. V.; Lyulin, A. V.; Lyulin, S. V. Coarse-Grained Molecular-Dynamics Simulations of Nanoparticle Diffusion in Polymer Nanocomposites. *Polymer (Guildf)* **2018**, *145*, 80–87.
- (68) Hagita, K.; Morita, H.; Doi, M.; Takano, H. Coarse-Grained Molecular Dynamics Simulation of Filled Polymer Nanocomposites under Uniaxial Elongation. *Macromolecules* **2016**, *49* (5), 1972–1983.
- (69) Yagyu, H. Simulations of the Effects of Filler Aggregation and Filler-Rubber Bond on the Elongation Behavior of Filled Cross-Linked Rubber by Coarse-Grained Molecular Dynamics. *Soft Mater.* **2017**, *15* (4), 263–271.
- (70) Furuya, T.; Koga, T. Molecular Simulation of Structures and Mechanical Properties of Nanocomposite Networks Consisting of Disk-Shaped Particles and Polymers. *Soft Matter* **2018**, *14* (41), 8293–8305.
- (71) Pasquini, M.; Raos, G. Tunable Interaction Potentials and Morphology of Polymer–Nanoparticle Blends. *J. Chem. Phys.* **2020**, *152* (17), 174902.
- (72) Rissanou, A. N.; Anastasiadis, S. H.; Bitsanis, I. A. A Monte Carlo Study of the Coil-to-Globule Transition of Model Polymer Chains near an Attractive Surface. *J. Polym. Sci., Part B: Polym. Phys.* **2009**, *47*, 2462–2476.
- (73) Low, J.; Yu, J.; Ho, W. Graphene-Based Photocatalysts for CO₂ Reduction to Solar Fuel. *J. Phys. Chem. Lett.* **2015**, *6*, 4244.
- (74) Fleischer, G. The Effect of Polydispersity on Measuring Polymer Self-Diffusion with the n.m.r. Pulsed Field Gradient Technique. *Polymer* **1985**, *26*, 1677–1682.
- (75) Peters, B. L.; Salerno, K. M.; Agrawal, A.; Perahia, D.; Grest, G. S. Coarse-Grained Modeling of Polyethylene Melts: Effect on Dynamics. *J. Chem. Theory Comput.* **2017**, *13* (6), 2890–2896.
- (76) Wang, Q.; Keffer, D. J.; Nicholson, D. M. A Coarse-Grained Model for Polyethylene Glycol Polymer. *J. Chem. Phys.* **2011**, *135* (21), 214903.
- (77) Akkermans, R. L. C.; Briels, W. J. A Structure-Based Coarse-Grained Model for Polymer Melts. *J. Chem. Phys.* **2001**, *114* (2), 1020–1031.
- (78) Panizon, E.; Bochicchio, D.; Monticelli, L.; Rossi, G. MARTINI Coarse-Grained Models of Polyethylene and Polypropylene. *J. Phys. Chem. B* **2015**, *119* (25), 8209–8216.
- (79) Rossi, G.; Monticelli, L.; Puisto, S. R.; Vattulainen, I.; Alani-Nissila, T. Coarse-Graining Polymers with the MARTINI Force-Field: Polystyrene as a Benchmark Case. *Soft Matter* **2011**, *7* (2), 698–708.
- (80) Wang, Y.; Jiang, W. E. I.; Yan, T.; Voth, G. a. Understanding Ionic Liquids through Atomistic and Coarse-Grained Molecular Dynamics Simulations. *Acc. Chem. Res.* **2007**, *40* (11), 1193–1199.
- (81) Dellago, C.; Bolhuis, P. G.; Geissler, P. L. *Computer Simulations in Condensed Matter Systems: From Materials to Chemical Biology*; Springer: 2006; Vol. 1; DOI: 10.1007/3-540-35273-2.
- (82) Harmandaris, V. A.; Kremer, K. Dynamics of Polystyrene Melts through Hierarchical Multiscale Simulations. *Macromolecules* **2009**, *42* (3), 791–802.
- (83) Wang, H.; Junghans, C.; Kremer, K. Comparative Atomistic and Coarse-Grained Study of Water: What Do We Lose by Coarse-Graining? *Eur. Phys. J. E* **2009**, *28* (2), 221–229.
- (84) Roux, B. The Calculation of the Potential of Mean Force Using Computer Simulations. *Comput. Phys. Commun.* **1995**, *91* (1–3), 275–282.
- (85) Marrink, S. J.; Risselada, H. J.; Yefimov, S.; Tieleman, D. P.; De Vries, A. H. The MARTINI Force Field: Coarse Grained Model for Biomolecular Simulations. *J. Phys. Chem. B* **2007**, *111* (27), 7812–7824.
- (86) Hagita, K.; Morita, H.; Doi, M.; Takano, H. Coarse-Grained Molecular Dynamics Simulation Approach for Polymer Nanocomposites Rubber. *Macromolecules* **2016**, *49* (5), 1972–1983.
- (87) Quan, X.; Peng, C.; Dong, J.; Zhou, J. Structural Properties of Polymer-Brush-Grafted Gold Nanoparticles at the Oil–Water Interface: Insights from Coarse-Grained Simulations. *Soft Matter* **2016**, *12* (14), 3352–3359.
- (88) Eslami, H.; Karimi-Varzaneh, H. A.; Müller-Plathe, F. Coarse-Grained Computer Simulation of Nanoconfined Polyamide-6,6. *Macromolecules* **2011**, *44*, 3117–3128.
- (89) Banerjee, P.; Roy, S.; Nair, N. Coarse-Grained Molecular Dynamics Force-Field for Polyacrylamide in Infinite Dilution Derived from Iterative Boltzmann Inversion and MARTINI Force-Field. *J. Phys. Chem. B* **2018**, *122* (4), 1516–1524.
- (90) Campos-Villalobos, G.; Siperstein, F. R.; Patti, A. Transferable Coarse-Grained MARTINI Model for Methacrylate-Based Copolymers. *Mol. Syst. Des. Eng.* **2019**, *4* (1), 186–198.
- (91) Spyriouni, T.; Tzoumanekas, C.; Theodorou, D.; Müller-Plathe, F.; Milano, G. Coarse-Grained and Reverse-Mapped United-Atom Simulations of Long-Chain Atactic Polystyrene Melts: Structure, Thermodynamic Properties, Chain Conformation, and Entanglements. *Macromolecules* **2007**, *40* (10), 3876–3885.
- (92) Li, Z.; Bian, X.; Yang, X.; Karniadakis, G. E. A Comparative Study of Coarse-Graining Methods for Polymeric Fluids: Mori-Zwanzig vs. Iterative Boltzmann Inversion vs. Stochastic Parametric Optimization. *J. Chem. Phys.* **2016**, *145* (4), 044102.
- (93) Schaeffle, K.; Ruiz Pestana, L.; Head-Gordon, T.; Lammers, L. N. A Structural Coarse-Grained Model for Clays Using Simple Iterative Boltzmann Inversion. *J. Chem. Phys.* **2018**, *148* (22), 222809.
- (94) Qian, H. J.; Carbone, P.; Chen, X.; Karimi-Varzaneh, H. A.; Liew, C. C.; Müller-Plathe, F. Temperature-Transferable Coarse-Grained Potentials for Ethylbenzene, Polystyrene, and Their Mixtures. *Macromolecules* **2008**, *41* (24), 9919–9929.
- (95) Reith, D.; Pütz, M.; Müller-Plathe, F. Deriving Effective Mesoscale Potentials from Atomistic Simulations. *J. Comput. Chem.* **2003**, *24* (13), 1624–1636.
- (96) Rossi, G.; Fuchs, P. F. J.; Barnoud, J.; Monticelli, L. A Coarse-Grained MARTINI Model of Polyethylene Glycol and of Polyoxyethylene Alkyl Ether Surfactants. *J. Phys. Chem. B* **2012**, *116* (49), 14353–14362.
- (97) Milano, G.; Goudeau, S.; Müller-Plathe, F. Multicentered Gaussian-Based Potentials for Coarse-Grained Polymer Simulations: Linking Atomistic and Mesoscopic Scales. *J. Polym. Sci., Part B: Polym. Phys.* **2005**, *43* (8), 871–885.

- (98) Li, Y.; Abberton, B. C.; Kröger, M.; Liu, W. K. Challenges in Multiscale Modeling of Polymer Dynamics. *Polymers* **2013**, *5* (2), 751–832.
- (99) Gooneie, A.; Schuschnigg, S.; Holzer, C. A Review of Multiscale Computational Methods in Polymeric Materials. *Polym.* **2017**, Vol. 9, Page 16 **2017**, *9* (1), 16.
- (100) Lee, H.; De Vries, A. H.; Marrink, S. J.; Pastor, R. W. A Coarse-Grained Model for Polyethylene Oxide and Polyethylene Glycol: Conformation and Hydrodynamics. *J. Phys. Chem. B* **2009**, *113* (40), 13186–13194.
- (101) Carbone, P.; Avendaño, C. Coarse-Grained Methods for Polymeric Materials: Enthalpy- and Entropy-Driven Models. *Wiley Interdiscip. Rev. Comput. Mol. Sci.* **2014**, *4* (1), 62–70.
- (102) Carbone, P.; Varzaneh, H. A. K.; Chen, X.; Müller-Plathe, F. Transferability of Coarse-Grained Force Fields: The Polymer Case. *J. Chem. Phys.* **2008**, *128* (6), 064904.
- (103) Abrams, C. F.; Delle Site, L.; Kremer, K. Dual-Resolution Coarse-Grained Simulation of the Bisphenol-[Formula Presented]-Polycarbonate/Nickel Interface. *Phys. Rev. E - Stat. Physics, Plasmas, Fluids, Relat. Interdiscip. Top.* **2003**, *67*, 021807.
- (104) Ghanbari, A.; Nodoro, T. V. M.; Leroy, F.; Rahimi, M.; Böhm, M. C.; Müller-Plathe, F. Interphase Structure in Silica-Polystyrene Nanocomposites: A Coarse-Grained Molecular Dynamics Study. *Macromolecules* **2012**, *45*, 572–584.
- (105) Garg, M.; Padmanabhan, V. Addition of P3HT-Grafted Silica Nanoparticles Improves Bulk-Heterojunction Morphology in P3HT-PCBM Blends. *Sci. Rep.* **2016**, *6*, No. 33219.
- (106) Huang, D. M.; Faller, R.; Do, K.; Moule, A. J. Coarse-Grained Computer Simulations of Polymer/Fullerene Bulk Heterojunctions for Organic Photovoltaic Applications. *J. Chem. Theory Comput.* **2010**, *6* (2), 526–537.
- (107) David, A.; Pasquini, M.; Tartaglino, U.; Raos, G. A Coarse-Grained Force Field for Silica–Polybutadiene Interfaces and Nanocomposites. *Polym.* **2020**, Vol. 12, Page 1484 **2020**, *12* (7), 1484.
- (108) Walker, C. C.; Genzer, J.; Santiso, E. E. Effect of Poly(Vinyl Butyral) Comonomer Sequence on Adhesion to Amorphous Silica: A Coarse-Grained Molecular Dynamics Study. *ACS Appl. Mater. Interfaces* **2020**, *12* (42), 47879–47890.
- (109) Bedrov, D.; Ayyagari, C.; Smith, G. D. Multiscale Modeling of Poly(Ethylene Oxide)–Poly(Propylene Oxide)–Poly(Ethylene Oxide) Triblock Copolymer Micelles in Aqueous Solution. *J. Chem. Theory Comput.* **2006**, *2* (3), 598–606.
- (110) Fischer, J.; Paschek, D.; Geiger, A.; Sadowski, G. Modeling of Aqueous Poly(Oxyethylene) Solutions. 2. Mesoscale Simulations. *J. Phys. Chem. B* **2008**, *112* (43), 13561–13571.
- (111) Moore, T. C.; Iacovella, C. R.; McCabe, C. Derivation of Coarse-Grained Potentials via Multistate Iterative Boltzmann Inversion. *J. Chem. Phys.* **2014**, *140* (22), 224104.
- (112) Moore, T. C.; Iacovella, C. R.; McCabe, C. Development of a Coarse-Grained Water Forcefield via Multistate Iterative Boltzmann Inversion. In *Foundations of Molecular Modeling and Simulation*; Springer: Singapore, 2016; pp 37–52; DOI: 10.1007/978-981-10-1128-3_3.
- (113) Chan, E. R.; Striolo, A.; McCabe, C.; Cummings, P. T.; Glotzer, S. C. Coarse-Grained Force Field for Simulating Polymer-Tethered Silsesquioxane Self-Assembly in Solution. *J. Chem. Phys.* **2007**, *127* (11), 114102.
- (114) Eslami, H.; Müller-Plathe, F. How Thick Is the Interphase in an Ultrathin Polymer Film? Coarse-Grained Molecular Dynamics Simulations of Polyamide-6,6 on Graphene. *J. Phys. Chem. C* **2013**, *117* (10), 5249–5257.
- (115) Pandey, Y. N.; Brayton, A.; Burkhart, C.; Papakonstantopoulos, G. J.; Doxastakis, M. Multiscale Modeling of Polyisoprene on Graphite. *J. Chem. Phys.* **2014**, *140* (5), 054908.
- (116) Ashbaugh, H. S.; Patel, H. A.; Kumar, S. K.; Garde, S. Mesoscale Model of Polymer Melt Structure: Self-Consistent Mapping of Molecular Correlations to Coarse-Grained Potentials. *J. Chem. Phys.* **2005**, *122* (10), 104908.
- (117) Hadley, K. R.; McCabe, C. A Coarse-Grained Model for Amorphous and Crystalline Fatty Acids. *J. Chem. Phys.* **2010**, *132* (13), 134505.
- (118) Maurel, G.; Goujon, F.; Schnell, B.; Malfreyt, P. Multiscale Modeling of the Polymer–Silica Surface Interaction: From Atomistic to Mesoscopic Simulations. *J. Phys. Chem. C* **2015**, *119* (9), 4817–4826.
- (119) Scocchi, G.; Posocco, P.; Fermeglia, M.; Pricl, S. Polymer - Clay Nanocomposites: A Multiscale Molecular Modeling Approach. *J. Phys. Chem. B* **2007**, *111* (9), 2143–2151.
- (120) Liu, J.; Zhang, L.; Cao, D.; Wang, W. Static, Rheological and Mechanical Properties of Polymer Nanocomposites Studied by Computer Modeling and Simulation. *Phys. Chem. Chem. Phys.* **2009**, *11* (48), 11365–11384.
- (121) Yuan, B.; Zeng, F.; Peng, C.; Wang, Y. Coarse-Grained Molecular Dynamics Simulation of Cis-1,4-Polyisoprene with Silica Nanoparticles under Extreme Uniaxial Tension. *Model. Simul. Mater. Sci. Eng.* **2021**, *29* (5), 055013.
- (122) Yuan, B.; Zeng, F.; Peng, C.; Wang, Y. Effects of Silica/Carbon Black Hybrid Nanoparticles on the Dynamic Modulus of Uncrosslinked Cis-1,4-Polyisoprene Rubber: Coarse-Grained Molecular Dynamics. *Polymer (Guildf)* **2022**, *238*, 124400.
- (123) Shere, I.; Adapa, S.; Malani, A. Development of Coarse-Grained Potential of Silica Species. *Model. Simul.* **2022**, *48* (15), 1343–1355.
- (124) Chaimovich, A.; Shell, M. S. Coarse-Graining Errors and Numerical Optimization Using a Relative Entropy Framework. *J. Chem. Phys.* **2011**, *134* (9), 094112.
- (125) Pretti, E.; Shell, M. S. A Microcanonical Approach to Temperature-Transferable Coarse-Grained Models Using the Relative Entropy. *J. Chem. Phys.* **2021**, *155* (9), 094102.
- (126) Izvekov, S.; Parrinello, M.; Burnham, C. J.; Voth, G. A. Effective Force Fields for Condensed Phase Systems from Ab Initio Molecular Dynamics Simulation: A New Method for Force-Matching. *J. Chem. Phys.* **2004**, *120* (23), 10896.
- (127) Ercolessi, F.; Adams, J. B. Interatomic Potentials from First-Principles Calculations: The Force-Matching Method. *EPL (Europhysics Lett.)* **1994**, *26* (8), 583.
- (128) Izvekov, S.; Voth, G. A. A Multiscale Coarse-Graining Method for Biomolecular Systems. *J. Phys. Chem. B* **2005**, *109* (7), 2469–2473.
- (129) Summers, A. Z.; Iacovella, C. R.; Cane, O. M.; Cummings, P. T.; McCabe, C. A Transferable, Multi-Resolution Coarse-Grained Model for Amorphous Silica Nanoparticles. *J. Chem. Theory Comput.* **2019**, *15* (5), 3260–3271.
- (130) Tóth, G. Effective Potentials from Complex Simulations: A Potential-Matching Algorithm and remarkson Coarse-Grained Potentials. *J. Phys.: Condens. Matter* **2007**, *19* (33), 335222.
- (131) Craven, N. C.; Gilmer, J. B.; Spindel, C. J.; Summers, A. Z.; Iacovella, C. R.; McCabe, C. Examining the Self-Assembly of Patchy Alkane-Grafted Silica Nanoparticles Using Molecular Simulation. *J. Chem. Phys.* **2021**, *154* (3), 034903.
- (132) Xia, W.; Song, J.; Jeong, C.; Hsu, D. D.; Phelan, F. R., Jr.; Douglas, J. F.; Keten, S. Energy-Renormalization for Achieving Temperature Transferable Coarse-Graining of Polymer Dynamics. *Macromolecules* **2017**, *50* (21), 8787–8796.
- (133) Patrone, P. N.; Rosch, T. W.; Phelan, F. R. Bayesian Calibration of Coarse-Grained Forces: Efficiently Addressing Transferability. *J. Chem. Phys.* **2016**, *144* (15), 154101.
- (134) Lee, C. K.; Hua, C. C. Nanoparticle Interaction Potentials Constructed by Multiscale Computation. *J. Chem. Phys.* **2010**, *132* (22), 224904.
- (135) Bejagam, K. K.; Singh, S.; An, Y.; Berry, C.; Deshmukh, S. A. PSO-Assisted Development of New Transferable Coarse-Grained Water Models. *J. Phys. Chem. B* **2018**, *122* (6), 1958–1971.
- (136) Yang, S.; Cui, Z.; Qu, J. A Coarse-Grained Model for Epoxy Molding Compound. *J. Phys. Chem. B* **2014**, *118* (6), 1660–1669.

- (137) Conway, O.; An, Y.; Bejagam, K. K.; Deshmukh, S. A. Development of Transferable Coarse-Grained Models of Amino Acids. *Mol. Syst. Des. Eng.* **2020**, *5* (3), 675–685.
- (138) McDonagh, J. L.; Shkurti, A.; Bray, D. J.; Anderson, R. L.; Pyzer-Knapp, E. O. Utilizing Machine Learning for Efficient Parameterization of Coarse Grained Molecular Force Fields. *J. Chem. Inf. Model.* **2019**, *59*, 4278–4288.
- (139) Kempfer, K.; Devémy, J.; Dequidt, A.; Couty, M.; Malfreyt, P. Multi-Scale Modeling of the Polymer–Filler Interaction. *Soft Matter* **2020**, *16* (6), 1538–1547.
- (140) Solano Canchaya, J. G.; Dequidt, A.; Garruchet, S.; Latour, B.; Martzel, N.; Devémy, J.; Goujon, F.; Blaak, R.; Schnell, B.; Munch, E.; Seeboth, N.; Malfreyt, P. Development of a Coarse-Grain Model for the Description of the Metal Oxide–Polymer Interface from a Bottom-up Approach. *J. Chem. Phys.* **2019**, *151* (6), 064703.
- (141) Solano Canchaya, J. G.; Clavier, G.; Garruchet, S.; Latour, B.; Martzel, N.; Devémy, J.; Goujon, F.; Dequidt, A.; Blaak, R.; Munch, E.; Malfreyt, P. Rheological Properties of Polymer Chains at a Copper Oxide Surface: Impact of the Chain Length, Surface Coverage, and Grafted Polymer Shape. *Phys. Rev. E* **2021**, *104* (2), 024501.
- (142) Marrink, S. J.; Tieleman, D. P. Perspective on the Martini Model. *Chem. Soc. Rev.* **2013**, *42* (16), 6801–6822.
- (143) Jeena, M. T.; Palanikumar, L.; Go, E. M.; Kim, I.; Kang, M. G.; Lee, S.; Park, S.; Choi, H.; Kim, C.; Jin, S. M.; Bae, S. C.; Rhee, H. W.; Lee, E.; Kwak, S. K.; Ryu, J. H. Mitochondria Localization Induced Self-Assembly of Peptide Amphiphiles for Cellular Dysfunction. *Nat. Commun.* **2017**, *8* (1), 1–10.
- (144) Van Eerden, F. J.; Melo, M. N.; Frederix, P. W. J. M.; Periole, X.; Marrink, S. J. Exchange Pathways of Plastoquinone and Plastoquinol in the Photosystem II Complex. *Nat. Commun.* **2017**, *8* (1), 1–8.
- (145) Yen, H. Y.; Hoi, K. K.; Liko, I.; Hedger, G.; Horrell, M. R.; Song, W.; Wu, D.; Heine, P.; Warne, T.; Lee, Y.; Carpenter, B.; Plückthun, A.; Tate, C. G.; Sansom, M. S. P.; Robinson, C. V. PtdIns(4,5)P₂ Stabilizes Active States of GPCRs and Enhances Selectivity of G-Protein Coupling. *Nat.* **2018**, *559* (7174), 423–427.
- (146) Abellón-Ruiz, J.; Kaptan, S. S.; Baslé, A.; Claudi, B.; Bumann, D.; Kleinekathöfer, U.; Van Den Berg, B. Structural Basis for Maintenance of Bacterial Outer Membrane Lipid Asymmetry. *Nat. Microbiol.* **2017**, *2* (12), 1616–1623.
- (147) Bruininks, B. M. H.; Souza, P. C. T.; Marrink, S. J. A Practical View of the Martini Force Field. *Methods Mol. Biol.* **2019**, *2022*, 105–127.
- (148) Vazquez-Salazar, L. I.; Selle, M.; De Vries, A. H.; Marrink, S. J.; Souza, P. C. T. Martini Coarse-Grained Models of Imidazolium-Based Ionic Liquids: From Nanostructural Organization to Liquid–Liquid Extraction. *Green Chem.* **2020**, *22* (21), 7376–7386.
- (149) Liu, J.; Qiu, L.; Alessandri, R.; Qiu, X.; Portale, G.; Dong, J. J.; Talsma, W.; Ye, G.; Sengrian, A. A.; Souza, P. C. T.; Loi, M. A.; Chiechi, R. C.; Marrink, S. J.; Hummelen, J. C.; Koster, L. J. A. Enhancing Molecular N-Type Doping of Donor–Acceptor Copolymers by Tailoring Side Chains. *Adv. Mater.* **2018**, *30* (7), 1704630.
- (150) Frederix, P. W. J. M.; Scott, G. G.; Abul-Hajja, Y. M.; Kalafatovic, D.; Pappas, C. G.; Javid, N.; Hunt, N. T.; Ulijn, R. V.; Tuttle, T. Exploring the Sequence Space for (Tri-)Peptide Self-Assembly to Design and Discover New Hydrogels. *Nat. Chem.* **2014**, *7* (1), 30–37.
- (151) Bochicchio, D.; Salvalaglio, M.; Pavan, G. M. Into the Dynamics of a Supramolecular Polymer at Submolecular Resolution. *Nat. Commun.* **2017**, *8* (1), 1–11.
- (152) Alessandri, R.; Grünewald, F.; Marrink, S. J. The Martini Model in Materials Science. *Adv. Mater.* **2021**, *33* (24), 2008635.
- (153) Marrink, S. J.; Mark, A. E. Molecular Dynamics Simulation of the Formation, Structure, and Dynamics of Small Phospholipid Vesicles. *J. Am. Chem. Soc.* **2003**, *125* (49), 15233–15242.
- (154) Buslaev, P.; Gushchin, I. Effects of Coarse Graining and Saturation of Hydrocarbon Chains on Structure and Dynamics of Simulated Lipid Molecules. *Sci. Rep.* **2017**, *7*, 11476.
- (155) Monticelli, L.; Kandasamy, S. K.; Periole, X.; Larson, R. G.; Tieleman, D. P.; Marrink, S. J. The MARTINI Coarse-Grained Force Field: Extension to Proteins. *J. Chem. Theory Comput.* **2008**, *4* (5), 819–834.
- (156) Souza, P. C. T.; Thallmair, S.; Conflitti, P.; Ramírez-Palacios, C.; Alessandri, R.; Raniolo, S.; Limongelli, V.; Marrink, S. J. Protein–Ligand Binding with the Coarse-Grained Martini Model. *Nat. Commun.* **2020**, *11* (1), 1–11.
- (157) Uusitalo, J. J.; Ingólfsson, H. I.; Akhshi, P.; Tieleman, D. P.; Marrink, S. J. Martini Coarse-Grained Force Field: Extension to DNA. *J. Chem. Theory Comput.* **2015**, *11* (8), 3932–3945.
- (158) López, C. A.; Rzepiela, A. J.; de Vries, A. H.; Dijkhuizen, L.; Hünenberger, P. H.; Marrink, S. J. Martini Coarse-Grained Force Field: Extension to Carbohydrates. *J. Chem. Theory Comput.* **2009**, *5* (12), 3195–3210.
- (159) Lutsyk, V.; Wolski, P.; Plazinski, W. Extending the Martini 3 Coarse-Grained Force Field to Carbohydrates. *J. Chem. Theory Comput.* **2022**, *18* (8), 5089–5107.
- (160) Uttarwar, R. G.; Potoff, J.; Huang, Y. Study on Interfacial Interaction between Polymer and Nanoparticle in a Nanocoating Matrix: A MARTINI Coarse-Graining Method. *Ind. Eng. Chem. Res.* **2013**, *52* (1), 73–82.
- (161) Gobbo, C.; Beurroies, I.; de Ridder, D.; Eelkema, R.; Marrink, S. J.; De Feyter, S.; van Esch, J. H.; de Vries, A. H. MARTINI Model for Physisorption of Organic Molecules on Graphite. *J. Phys. Chem. C* **2013**, *117* (30), 15623–15631.
- (162) Marrink, S. J.; De Vries, A. H.; Mark, A. E. Coarse Grained Model for Semiquantitative Lipid Simulations. *J. Phys. Chem. B* **2004**, *108* (2), 750–760.
- (163) Souza, P. C. T.; Alessandri, R.; Barnoud, J.; Thallmair, S.; Faustino, I.; Grünewald, F.; Patmanidis, I.; Abdizadeh, H.; Bruininks, B. M. H.; Wassenaar, T. A.; Kroon, P. C.; Melcr, J.; Nieto, V.; Corradi, V.; Khan, H. M.; Domański, J.; Javanainen, M.; Martinez-Seara, H.; Reuter, N.; Best, R. B.; Vattulainen, I.; Monticelli, L.; Periole, X.; Tieleman, D. P.; de Vries, A. H.; Marrink, S. J. Martini 3: A General Purpose Force Field for Coarse-Grained Molecular Dynamics. *Nat. Methods* **2021**, *18* (4), 382–388.
- (164) Lee, H.; de Vries, A. H.; Marrink, S.; Pastor, R. W. A Coarse-Grained Model for Polyethylene Oxide and Polyethylene Glycol: Conformation and Hydrodynamics. *J. Phys. Chem. B* **2009**, *113* (40), 13186–13194.
- (165) Pantawane, S.; Gekle, S. Temperature-Dependent Conformation Behavior of Isolated Poly(3-Hexylthiophene) Chains. *Polymers (Basel)* **2022**, *14* (3), 550.
- (166) Brosz, M.; Michelarakis, N.; Bunz, U. H. F.; Aponte-Santamaría, C.; Gräter, F. Martini 3 Coarse-Grained Force Field for Poly(Para-Phenylene Ethynylene)S. *Phys. Chem. Chem. Phys.* **2022**, *24* (17), 9998–10010.
- (167) Alessandri, R.; Sami, S.; Barnoud, J.; de Vries, A. H.; Marrink, S. J.; Havenith, R. W. A. Resolving Donor–Acceptor Interfaces and Charge Carrier Energy Levels of Organic Semiconductors with Polar Side Chains. *Adv. Funct. Mater.* **2020**, *30* (46), 2004799.
- (168) Winands, T.; Böckmann, M.; Schemme, T.; Ly, P. M. T.; De Jong, D. H.; Wang, Z.; Denz, C.; Heuer, A.; Doltsinis, N. L. P3HT:DiPBI Bulk Heterojunction Solar Cells: Morphology and Electronic Structure Probed by Multiscale Simulation and UV/Vis Spectroscopy. *Phys. Chem. Chem. Phys.* **2016**, *18* (8), 6217–6227.
- (169) Rolland, N.; Modarresi, M.; Franco-Gonzalez, J. F.; Zozoulenko, I. Large Scale Mobility Calculations in PEDOT (Poly(3,4-Ethylenedioxythiophene)): Backmapping the Coarse-Grained MARTINI Morphology. *Comput. Mater. Sci.* **2020**, *179*, 109678.
- (170) Modarresi, M.; Mehandziyski, A.; Fahlman, M.; Tybrandt, K.; Zozoulenko, I. Microscopic Understanding of the Granular Structure and the Swelling of PEDOT:PSS. *Macromolecules* **2020**, *53* (15), 6267–6278.
- (171) Jain, K.; Mehandziyski, A. Y.; Zozoulenko, I.; Wågberg, L. PEDOT:PSS Nano-Particles in Aqueous Media: A Comparative

- Experimental and Molecular Dynamics Study of Particle Size, Morphology and z-Potential. *J. Colloid Interface Sci.* **2021**, *584*, 57–66.
- (172) Shmilovich, K.; Mansbach, R. A.; Sidky, H.; Dunne, O. E.; Panda, S. S.; Tovar, J. D.; Ferguson, A. L. Discovery of Self-Assembling π -Conjugated Peptides by Active Learning-Directed Coarse-Grained Molecular Simulation. *J. Phys. Chem. B* **2020**, *124* (19), 3873–3891.
- (173) Mansbach, R. A.; Ferguson, A. L. Coarse-Grained Molecular Simulation of the Hierarchical Self-Assembly of π -Conjugated Optoelectronic Peptides. *J. Phys. Chem. B* **2017**, *121* (7), 1684–1706.
- (174) Li, J.; Zhang, Q.; Yan, L.; Wu, G.; Hu, M.; Lin, X.; Yuan, K.; Yang, X. Ultrafast Flash Energy Conductance at MXene-Surfactant Interface and Its Molecular Origins. *Adv. Mater. Interfaces* **2019**, *6* (23), 1901461.
- (175) Wallace, E. J.; Sansom, M. S. P. Carbon Nanotube/Detergent Interactions via Coarse-Grained Molecular Dynamics. *Nano Lett.* **2007**, *7* (7), 1923–1928.
- (176) Lee, H. Molecular Dynamics Studies of PEGylated Single-Walled Carbon Nanotubes: The Effect of PEG Size and Grafting Density. *J. Phys. Chem. C* **2013**, *117* (49), 26334–26341.
- (177) Lin, S.; Zhang, J.; Strano, M. S.; Blankschtein, D. Understanding Selective Molecular Recognition in Integrated Carbon Nanotube–Polymer Sensors by Simulating Physical Analyte Binding on Carbon Nanotube–Polymer Scaffolds. *Soft Matter* **2014**, *10* (32), 5991–6004.
- (178) Shi, M.; Yang, W.; Zhang, Y.; Tan, J.; Cheng, L.; Jiao, Z.; Zhen, X. Mechanical and Dielectric Properties and Crystalline Behavior of Multilayer Graphite-Filled Polyethylene Composites. *J. Appl. Polym. Sci.* **2019**, *136* (42), 48131.
- (179) Dong, J.; Zhou, J. Solvent-Responsive Behavior of Polymer-Brush-Modified Amphiphilic Gold Nanoparticles. *Macromol. Theory Simulations* **2013**, *22* (3), 174–186.
- (180) Dong, J.; Li, J.; Zhou, J. Interfacial and Phase Transfer Behaviors of Polymer Brush Grafted Amphiphilic Nanoparticles: A Computer Simulation Study. *Langmuir* **2014**, *30* (19), 5599–5608.
- (181) Dahal, U.; Wang, Z.; Dormidontova, E. E. Hydration of Spherical PEO-Grafted Gold Nanoparticles: Curvature and Grafting Density Effect. *Macromolecules* **2018**, *51* (15), 5950–5961.
- (182) Dahal, U.; Dormidontova, E. E. Chain Conformation and Hydration of Polyethylene Oxide Grafted to Gold Nanoparticles: Curvature and Chain Length Effect. *Macromolecules* **2020**, *53* (19), 8160–8170.
- (183) Perrin, E.; Schoen, M.; Coudert, F.-X.; Boutin, A. Structure and Dynamics of Solvated Polymers near a Silica Surface: On the Different Roles Played by Solvent. *J. Phys. Chem. B* **2018**, *122* (16), 4573–4582.
- (184) Heinz, H.; Koerner, H.; Anderson, K. L.; Vaia, R. A.; Farmer, B. L. Force Field for Mica-Type Silicates and Dynamics of Octadecylammonium Chains Grafted to Montmorillonite. *Chem. Mater.* **2005**, *17* (23), 5658–5669.
- (185) Suter, J. L.; Coveney, P. V. Chemically Specific Multiscale Modeling of the Shear-Induced Exfoliation of Clay-Polymer Nanocomposites. *ACS Omega* **2018**, *3* (6), 6439–6445.
- (186) Alessandri, R.; Souza, P. C. T.; Thallmair, S.; Melo, M. N.; De Vries, A. H.; Marrink, S. J. Pitfalls of the Martini Model. *J. Chem. Theory Comput.* **2019**, *15* (10), 5448–5460.
- (187) Foley, T. T.; Shell, M. S.; Noid, W. G. The Impact of Resolution upon Entropy and Information in Coarse-Grained Models. *J. Chem. Phys.* **2015**, *143* (24), 243104.
- (188) Brini, E.; Algaer, E. A.; Ganguly, P.; Li, C.; Rodríguez-Roperio, F.; Van Der Vegt, N. F. A. Systematic Coarse-Graining Methods for Soft Matter Simulations – a Review. *Soft Matter* **2013**, *9* (7), 2108–2119.
- (189) Wagner, J. W.; Dama, J. F.; Durumeric, A. E. P.; Voth, G. A. On the Representability Problem and the Physical Meaning of Coarse-Grained Models. *J. Chem. Phys.* **2016**, *145* (4), 044108.