

NEW METHODS, TOOLS AND TECHNIQUES FOR THE EVOLUTIONARY
DETERMINATION OF ENSEMBLES OF PARETO EFFICIENT
PARAMETERIZATIONS OF CLASSICAL POTENTIALS WITH APPLICATIONS

By
EUGENE RAGASA

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I dedicate this to everyone that helped revamp this template. Aliquam molestie sed urna quis convallis. Aenean nibh eros, aliquam non eros in, tempus lacinia justo. In magna sapien, blandit a faucibus ac, scelerisque nec purus. Praesent fermentum felis nec massa interdum, vel dapibus mi luctus. Cras id fringilla mauris. Ut molestie eros mi, ut hendrerit nulla tempor et. Pellentesque tortor quam, mattis a scelerisque nec, euismod et odio. Mauris rhoncus metus sit amet risus mattis, eu mattis sem interdum.

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Thanks to all the help I have received in writing and learning about this tutorial. Acknowledgments are required and must be written in paragraph form. This mandates at least three sentences.

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Abstract of Dissertation Presented to the Graduate School
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Requirements for the Degree of Doctor of Philosophy

NEW METHODS, TOOLS AND TECHNIQUES FOR THE EVOLUTIONARY
DETERMINATION OF ENSEMBLES OF PARETO EFFICIENT
PARAMETERIZATIONS OF CLASSICAL POTENTIALS WITH APPLICATIONS

By

Eugene Ragasa

May 2016

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Major: Materials Science and Engineering

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CHAPTER 1 INTRODUCTION

As computational power has increased so has the size and complexity of the simulations.

The use of analytical empirical potentials has been part of computational materials science from the start, including problems with lattice dynamics, molecular dynamics, and other charges.

Despite the promise of molecular dynamics, the difficulty in developing interatomic potentials leads to long developments when developing empirical potentials due to problems in determining an optimal parameterization.

This work presents an emergent framework for the automated development of potentials based upon sampling from a distribution and evolution of that distribution so that the final distribution represents the set of parameterizations which can be described in a way as efficient.

We present an novel framework for the automated development of potentials.

1.1

1.2 Modernizing Analytical Potential Development

The modernization of analytical potential development needs to provide: (1) clearly define the problem in its most general terms in what maybe, at times, in a more rigorous mathematical exposition than what is normally presented, (2) identify the problems with existing methodologies by bringing in terminology and notation from different fields to provide a more general framework for the problem of potential development, (3) provide a baseline implementation of this framework, which while begin largely pedagogical provides results which are analytical, transparent, and robust, and (4) provide an automation framework upon which to do the work.

This work starts with an appropriate level of introduction to the major toolsets in computational materials science in Chapter 2, where we start from a quantum mechanical

approaches to solutions to the potential energy surface, a function which maps the configuration space of atomic descriptors onto energies, focusing specifically on Density Functional Theory, which is often used to augment (and often completely replaces) experimental observations. From here, we look to two tools where analytical potentials are most often used (1) molecular dynamic simulations, and (2) lattice dynamics simulations. For completeness, a discussion of higher level tools and how these tools are necessary to bridge scale.

In the third chapter, the empirical interatomic potential is described as approximation as the potential energy surface. In the traditional approach to potential development, an objective function described as the weighted sum of square differences between the analytical potential predicted values for a finite set of material properties and their respective target values, a set property structure relationships which are known as the fitting database. This objective function is minimized usually through either constrained or unconstrained optimization techniques dependent upon a quadratic programming algorithm dependent upon first-order derivatives for optimization. In this chapter, we show that this method for even identifying the global minimum due to issues with (1) regularization, (2) necessary conditions for a solution are likely not satisfied (Karush-Kuhn-Tucker conditions), and at the very least impossible to prove. As a result, quadratic programming techniques are likely unsuitable, except when an initial guess to the target parameterization is already known. This problem is hinted at in discussions in literature in discussions in a move from local optimization vs global optimization algorithms. However, more damning is that even when these conditions are met, the optimal parameterization is dependent upon a vector of weights, which uniquely determines the parameterization. That is, potential development is inherently a subjective process dependent upon the preferences of the user, which largely cannot be determined with certainty at the beginning of the process.

The ramification of chapter 3 is that potential optimization is NP-hard when preferences are fixed is that probing acceptable potentials by a mechanism of varying weights is computationally brutal, and reevaluates areas in parameter space which have already been solved. Chapter 4 starts a framework for sampling in parameter space beginning with statistical concepts and links it to approaches in machine learning with genetic algorithms.

This work first starts with what is hoped an appropriate level of theory required to understand the necessities for automating the problem. In much of the literature, there is rather extensive discussion of techniques and applications of techniques, but the supporting justification and rationalization of these techniques is necessarily short due to the format of publications. Even when discussing older approaches, appropriate review articles have been identified from different fields into order to provide insight to the problem of potential development.

In the development of a solid methodology and a description of potential development automation, it is necessary first describe the major computational tools used within the framework of machine learning. Specifically, the tools of Density Functional Theory, Molecular Dynamics, and Lattice Dynamics are briefly discussed to provide a sense of what is common and what is different between these computational approaches. This is covered in chapter 2.

Chapter 3 describes which to is referred to the the traditional approach to potential development. Potential development is normally described as a quadratic programming optimization problem, applied to a description of a problem which it is not normally suited for. However, this problem has never really been discussed clearly and explains why more recently many potential developers have moved from potential development

ather than being competitive, *ab initio* computational techniques are often integrated into potential development Despite promising work with the development of machine learning potentials, which drastically increases the size of the functional space to describe

a potential energy surface, these approaches require large amounts of computational resources to develop the requisite fitting datasets. This data is necessary for this data hungry approach as into ensure that the problem is not in functionally underdetermined due to large degrees of freedom associated with the functional form. Moreover, neural networks models themselves are NP-hard problems which maps the current configuration of the neural net onto potential configuration space, requiring an extraordinary computational effort to determine the most effective parameter optimization. It should not be confused that neural networks are not an optimization solution, but actually an optimization problem, which are aided by different machine learning techniques which are dependent upon sampling

This work takes a contrary, but complimentary approach by addressing the concerns readily brought force by this new avenue of study. The promise of machine learning potentials is provide *ab initio* level accuracy at a fraction of the cost of *ab initio* techniques.

It is the opinion of the author, that the development of analytical empirical potentials has largely been retarded by the lack of standard tools and analytical frameworks. Despite the ubiquity of molecular dynamics Instead of looking to develop the optimal parameterization which is expected to replicate a large range of values. We accept that the development of an potential largely involves a decision of tradeoffs determined by the potential developer, these expression of preferences is inherently subjective.

Instead of developing a large monolithic application, which is difficult to extend, modify, and implement. Pypospack is conceived largely as software library which defines structure property relationships, how the structure property relationships are calculated, the process management of molecular dynamic simulations, parallel sampling, and potential selection.

CHAPTER 2

THE MANY BODY PROBLEM AND ATOMISTIC METHODS

The properties of a system may be obtained by solving the quantum mechanical (QM) wave equation which governs the system dynamics. For non-relativistic system, this equation is the Schrodinger's equation. For all but the simplest systems, this approach is an impossible task in practice; the resulting many body problem has only been solved for a limited number of system. Within this chapter we outline the many body problem, it's intractability before considering the Hohenberg-Kohn-Sham formulation of density functional theory (DFT), particularly in it's formulation it's application for systems with periodic boundary conditions. This reformulates quantum mechanics, using electron density as the fundamental parameter to solve, rather than the many-electron wavefunction. This takes the N -body problem and recasts it into N single-body problems; which is a dramatic simplification.

We then approach higher order models which reduces computational intensity by looking at classical empirical potentials and their role in both molecular dynamics and lattice dynamics.

2.1 The Many-Body Problem

2.1.1 Born-Oppenheimer Approximation

The Born-Oppenheimer approximation [1] is ubiquitous in *ab initio* calculations, and forms the justification for classical empirical potentials.

2.2 Interatomic Potentials

The justification for the use of classical empirical potentials can be demonstrated from the Born-Oppenheimer approximation[1] The Hamiltonian for a real material is defined by the presence of interacting nuclei and electrons:

$$H = \sum_i \frac{P_i^2}{2M_i} + \sum_\alpha \frac{p_\alpha^2}{2m} + \frac{1}{2} \sum_{ij} \frac{Z_i Z_j e^2}{r_{ij}} + \frac{1}{2} \sum_{\alpha\beta} \frac{e^2}{r_{\alpha\beta}} - \sum_{i\alpha} \frac{Z_i e^2}{r_{i\alpha}} \quad (2-1)$$

The first terms are kinetic energy terms, the latter terms are the nuclei-nuclei, electron-electron, and nuclei-electron interactions. Ideally, the solution of Schrödinger's equation, $H\Psi = E\Psi$ could be solved providing the total wavefunction $\Psi(\mathbf{r}_i, \mathbf{r}_\alpha)$. Except for the simplest of systems, this approach is impossible computationally. This later equation does not contain any electronic degrees of freedom, because all electronic effects are incorporated into $U(\mathbf{R}_i)$ which is the interatomic potential. For molecular dynamics, Schrödinger's equation is replaced with Newton's equation of motion.

The kinetic energy is ignored since the heavy nuclei move more slowly than electrons. For the remaining interaction terms of the Hamiltonian, the nuclear positions are clamped at certain positions in space, the electron-nuclei interactions are not removed, since the electrons are still influenced by the Coulomb potential of the nuclei. This allows us to factor the wavefunction as

$$\Psi(\mathbf{R}_i, \mathbf{r}_\alpha) = \Xi(\mathbf{R}_i)\Phi(\mathbf{r}_\alpha; \mathbf{R}_i) \quad (2-2)$$

, where $\Xi(\mathbf{R}_i)$ describes the nuclei, and $\Phi(\mathbf{r}_\alpha; \mathbf{R}_i)$ describes the electrons parameterized by the clamped position of \mathbf{R}_i . In turn, the Hamiltonian is solve able as two Schrödinger's equations. The first equation contains the electronic degrees of freedom.

$$H_e\Phi(\mathbf{r}_\alpha; \mathbf{R}_i) = U(\mathbf{R}_i)\Phi(\mathbf{r}_\alpha; \mathbf{R}_i) \quad (2-3)$$

where

$$H_e = \sum_{\alpha} \frac{p_{\alpha}^2}{2m} + \frac{1}{2} \sum_{ij} \frac{Z_i Z_j e^2}{r_{ij}} + \frac{1}{2} \sum_{\alpha\beta} \frac{e^2}{r_{\alpha\beta}} - \sum_{i\alpha} \frac{Z_i e^2}{r_{i\alpha}} \quad (2-4)$$

Eqn. 2-3 gives the energy $U(\mathbf{R}_i)$ which depends on the clamped coordinates of \mathbf{R}_i . The electronic effects are contained in $U(\mathbf{R}_i)$ and is incorporated into the second equation which the motion of the nuclei

$$H_n\Xi(\mathbf{R}_i) = E\Xi(\mathbf{R}_i) \quad (2-5)$$

where

$$H_n = \sum_i \frac{P_i^2}{2m_i} + U(\mathbf{R}_i) \quad (2-6)$$

2.3 Density Functional Theory

Density Functional Theory is a simplification of the many body electron function by relating the wave function of the system of interest to the electron density of the system, where the firm theoretical underpinning are established by the Hohenberg-Kohn theorems[2].

The first Hohenberg-Kohn theorem demonstrates that the ground state properties of a many electron system are uniquely determined by an electron density that only depends on the three spatial coordinates. This reduces the many-body problem of N electrons with $3N$ spatial coordinates to three spatial coordinates, through the use of functionals of the electron density.

The second Hohenberg-Kohn theorem defines an energy functional and proves that the correct ground electron density also minimizes this energy functional. Since DFT is a ground state

2.3.1 The Exchange Correlation Term

2.4 Density Functional Theory for Solids

2.4.1 Representation of an Infinite Solid

The potential energy, V is only dependent upon the relative internal coordinates of the system. For a system with N atoms indexed by i , there are $3N$ total coordinates for the system, $\mathbf{r}_i = (r_{i1}, r_{i2}, r_{i3})$ In the absence of an external field, an atomic system potential energy is invariant of translations and rotations in space.

2.4.2 Bloch's Theorem

2.4.3 Plane Wave Formulation

2.4.4 k-point sampling

2.5 Empirical Interatomic Potentials

The interatomic potential $U(\mathbf{R}_i)$ derived from the Born-Oppenheimer approximation is derived from a quantum-mechanical perspective. The computational cost of *ab initio*

such as density-functional theory (DFT) can provide accurate structural energies and forces, but their computational cost limits approaches to compute $U(\mathbf{R}_i)$ makes the scientific inquiry of systems requiring longer simulation times or larger number of atoms to captures relevant feature sizes unreasonable. An empirical interatomic potential $V(\mathbf{R}_i; \boldsymbol{\theta})$ is an analytical function parameterized by $\boldsymbol{\theta} = (\theta_1, \dots, \theta_n)$ which is meant to approximate $U(\mathbf{R}_i)$. The total energy of a potential of N atoms with an interaction described by the empirical potential, V , can be expanded in a many body expansion.

$$V(\mathbf{r}_1, \dots, \mathbf{r}_N) = \sum_i V_1(\mathbf{r}_i) + \sum_i \sum_{i < j} V_2(\mathbf{r}_i, \mathbf{r}_j) + \sum_i \sum_{i < j} \sum_{j < k} V_3(\mathbf{r}_i, \mathbf{r}_j, \mathbf{r}_k) + \dots \quad (2-7)$$

The first term V_1 is the one body term, due to an external field or boundary conditions, which is typically ignored in classical potentials. The second term V_2 is the pair potential, the interaction of the term is dependent upon the distance between \mathbf{r}_i and \mathbf{r}_j . The three-body term potential V_3 arises when the interaction interaction of a pair of atoms is modified by the presence of a third. Based upon this expansion, we can classify certain potentials into two classes: pair potentials when only V_2 is present and many-body potentials when V_3 and higher order terms are included.

Over the last few decades, a large number of potentials have been developed to descibe various bonding types and environments. To take representative examples, the Lennard Jones was developed for the van der Waals interactions of noble gases, pair potentials such as the Buckingham potential can be used for ionic solids, the embedded atom model (EAM) is developed for metallic systems, the Assisted Model Building with Energy Refinement (AMBER) for biomolecules, the tersoff potential for covalently bonded materials. To deal with bonding and chemical environments for heterogenous materials like metal/metal oxide interfaces have led to extensions such as MEAM, REBO, COMB, and ReaxFF.

More recently, potentials such as GAP and SNAP represent the atomic environment of an atom not from a collection of a vectors of atomic positions which feed into formulaic

functional forms, but to calculate the bispectrum of the neighborhood of atoms. The bispectrum combined with an orthogonal expansion of components is dependent upon large amounts of density functional images to use in the fitting dataset to produce DFT fidelity reproductions of interatomic forces on an atom.

2.5.1 Pair Potentials

2.5.1.1 Leonnard Jones

2.5.1.2 Coulomb Potential

2.5.1.3 Born-Mayer Potential

2.5.1.4 Morse Potential

2.5.1.5 Buckingham Potential

2.5.2 Many Body Potentials

2.5.2.1 Tersoff Potentials

2.5.2.2 Stillinger Weber Potentials

2.5.2.3 Embedded Atom Method Potentials

This chapter reviews typical approaches to fitting empirical potentials.

2.6 Molecular Dynamics

Molecular dynamics (MD) is a simulation approach where the time evolution of a set of interacting atoms is followed by numerically solving their equations of motion. In MD, the behavior of atoms follows Newtonian mechanics:

$$M \frac{d\mathbf{r}(t)}{dt} = F(\mathbf{r}(t)) = -\nabla V(\mathbf{r}(t)) \quad (2-8)$$

where t is time, $\mathbf{r}(t) = (\mathbf{r}_1(t), \mathbf{r}_2(t), \dots, \mathbf{r}_N(t))$ represents the forces on the particles, and M is the mass matrix, which is a diagonal matrix with the mass, m_k , for $M_{k,k} = m_k$ for all diagonal entries. The total energy is conserved, even if the kinetic energy and potential energy can change dynamically. In Hamiltonian form, the Newtonian equation of motion

can be written Hamiltonian form (Allen, Tildesley, et al 1989).

$$\frac{d\mathbf{r}}{dt} = \frac{\partial H(\mathbf{r}, \mathbf{p})}{\partial \mathbf{p}}, \frac{d\mathbf{p}}{dt} = -\frac{\partial H(\mathbf{r}, \mathbf{p})}{\partial \mathbf{r}} \quad (2-9)$$

Therefore,

$$\frac{dH}{dt} = \frac{\partial H(\mathbf{r}, \mathbf{p})}{\partial \mathbf{r}} \frac{d\mathbf{r}}{dt} + \frac{\partial H(\mathbf{r}, \mathbf{p})}{\partial \mathbf{p}} \frac{d\mathbf{p}}{dt} = 0 \quad (2-10)$$

2.6.1 Numerical Integration

A dynamical simulation computes atomic positions as a function of time given their initial position $\mathbf{r}(t = 0)$ and velocities $\mathbf{v}(t = 0)$. Since Newton's equations of motion are 2nd order differential equations, an initial condition needs to specify both positions and velocities of all atoms at the initial condition. To solve the equation of motion computationally, we need to discretize time. Usually, time is discretized uniformly, $t_n = n\Delta t$, where Δt is referred to as the time step. The task of the simulation algorithm is to find $\mathbf{r}(t_n)$ for $i = 1, 2, 3, \dots$ (Allen, Tildesley *et al* 1989).

The Verlet algorithm begins by approximating

$$\frac{d^2\mathbf{r}(t)}{dt^2} = \frac{\mathbf{r}(t + \Delta t) - 2\mathbf{r}(t) + \mathbf{r}(t - \Delta t)}{\Delta t^2} \quad (2-11)$$

Thus,

$$\frac{\mathbf{r}(t + \Delta t) - 2\mathbf{r}(t) + \mathbf{r}(t - \Delta t)}{\Delta t^2} = -\frac{1}{m} \frac{dU(\mathbf{r}(t))}{d\mathbf{r}} \quad (2-12)$$

$$\mathbf{r}(t + \Delta t) = 2\mathbf{r}(t) - \mathbf{r}(t - \Delta t) - \Delta t^2 \frac{1}{m} \frac{dU(\mathbf{r}(t))}{d\mathbf{r}} \quad (2-13)$$

2.6.2 Thermodynamic Ensembles

2.6.2.1 Microcanonical (NVE) ensemble

2.6.2.2 Canonical (NVT) ensemble

2.6.2.3 NPT

2.7 Lattice Dynamics

2.8 Calculation of Material Properties

2.8.1 Structural Properties

2.8.1.1 Minimization Techniques

Greatest Descent Conjugate Gradient

2.8.2 Phase Order Properties

2.8.3 Point Defect Formation Energies

2.8.4 Surface Energies

2.8.5 Stacking Fault Energies

2.9 Notation

2.9.1 Simulation Cell

A simulation cell is defined by the lattice basis and the atomic basis. The lattice vectors which describes the periodic boundary conditions three lattice vectors $\mathbf{a}, \mathbf{b}, \mathbf{c}$ Euclidean space which forms the basis for the crystallographic system when periodic boundary conditions are applied. The translational properties of a crystal allows the simulation of an infinite bulk material from a fixed volume. In traditional crystallography, the boundaries of the unit cell were defined as a, b, c corresponding to the length of each lattice vector and the angles α, β, γ . In computational materials, a more convenient representation

CHAPTER 3

PARETO OPTIMALITY AND POTENTIAL DEVELOPMENT

In the previous chapter, an overview of the different computational tools associated to atomistic simulation were presented to give some idea of interconnectivity and breath of atomistic simulations. Within this chapter, we outline the Pareto approach to potential optimization within the context of more typical current approaches to potential development.

The structure of this chapter starts off by framing potential development the broadest mathematical framework possible since the purpose of this dissertation is to identify new techniques and directions for potential development which have been enabled by a broad set of computational tools which harnesses large amounts of computational power to solve analytically intractable problems in a field broadly known as machine learning.

This chapter consists of three sections. In the first section, we introduce the idea of a potential energy surface and how interatomic potentials can be thought of as computational inexpensive surrogate models, and we introduce the terminology of potential development as well as some broad concepts of potential optimization. Next, we build up the notation and terminology of general optimization from a broad mathematical standpoint, first covering the more familiar single-objective optimization then multiobjective optimization. In the third section, we combine the discussion of the first and second section, to cast the problem of potential development as a multi-objective optimization utilizing the concepts and notation common to most. In particular, we discuss the the current techniques to potential optimization which are applied to potential optimization as well as some of the mathematical problems and issues of certain approach, and then clearly demonstrate that multi-objective optimization is dependent upon the concept of Pareto optimality.

3.1 Potential Energy Surfaces

The potential energy surface is the energy of a collection of atoms as a function of the positions of its nuclei, $\{\mathbf{R}\}$. Using the analogy of a landscape, the potential energy surface (PES) represents a mapping of the positions of the atoms of a material system to an energies. This creates an energy landscape which allows materials systems to viewed from a topological perspective, which allows the PES to describe the evolution of a system.

From a mathematical representation, the PES is a a function, $V : \mathbf{R} \rightarrow E$, which maps a high dimensional interatomic configuration, \mathbf{R} , onto the set of real numbers representing energies, $E \in \mathbb{R}$. To describe empirical potentials, we first start with a mathematical description of configuration space both from a crystallographic perspective, but how this crystallgraphic perspective can be translated into other representation common with empirical potentials.

Next we discuss

3.1.1 Configuration Space

In solid materials, atoms are typically represented as infinite crystalline solids, with th atomic positions placed within a representative unit. This representative unit is referred to as a unit cell, which defines that boundaries, the volume, the lattice positions of each atom.

The boundaries of the unit cell are defined are defined by three lattice vectors, defined in three dimensional Euclidean space, \mathbb{R}^3 . Thethe three lattice vectors, \mathbf{a}_1 , \mathbf{a}_2 , and \mathbf{a}_3 , with $\mathbf{a}_i \in \mathbb{R}^3$. Each atom i is identified by a chemical species, and its atomic position $\mathbf{r}_i = \{r_1, r_2, r_3\}$, where $\mathbf{a}_1 \in \mathbb{R}^3$, which defines the boundaries of the representative cell, and periodic boundaries conditions applied to reflects the translational symmetry of crystalline systems. Each lattice vector can be represented as a translational operator, T_i for $i = 1, 2, 3$, such that, $T_i(\mathbf{r} = \mathbf{r})$

$$T(\mathbf{r}_i) = \mathbf{r}_i + n_1\mathbf{a}_1 + n_2\mathbf{a}_2 + n_3\mathbf{a}_3, \forall i \in \mathbb{Z} \quad (3-1)$$

3.1.2 Pair Wise Interactions

3.1.3 Three Body Interactions

3.1.4 Many Body Interactions

Given an atomic arrangement \mathbf{r} , $V(\mathbf{R})$ gives the height of the energy landscape for any atomic configuration, providing an analytical approximation of the potential energy surface, so that the concept of a potential energy surface arises. To study the evolution of a system, such as kinetic properties and chemical reactions, it is necessary to calculate the energy for every atomic arrangement of interest.

The geometry of a molecule can be described by the collection of the positions of N atoms $\mathbf{R} = \{\mathbf{r}_1, \dots, \mathbf{r}_N\}$, where the \mathbf{r}_i could be the set of Cartesian coordinates of the atoms. These collections of atoms can be transformed to reflect the distances between the two atoms i and j , $\mathbf{r}_{ij} = \mathbf{r}_i - \mathbf{r}_j$ as used in pair potentials, the angles between atoms \mathbf{r}_{ijk} as in three body potentials.

3.2 Empirical Interatomic Potentials

The goal of developing a interatomic potential is identify a computationally efficient surrogate model, which models the potential energy surface.

$$V(\mathbf{R}) = \hat{V}(\mathbf{R}) + \epsilon(\mathbf{R}) \quad (3-2)$$

Here V is the true potential energy surface which is approximated by our potential model \hat{V} , which is a function the representation of a collection of atomic positions, \mathbf{R} . Throuhout this work, the use of the hat over a variable indicates that the quantity is an approximation of the actual value. Since energy is a scalar value, the difference between the potential energy surface we will refer to as the error function,

$$\epsilon(\mathbf{R}) = V(\mathbf{R}) - \hat{V}(\mathbf{R}). \quad (3-3)$$

With an empirical potential, \hat{V} , is parameterized by a vector of N values, $\boldsymbol{\theta} = \{\theta_1, \dots, \theta_N\}$. In the forward use of a potential, the parameters are considered to be fixed, $\hat{V}(\mathbf{R} : \boldsymbol{\theta})$,

where the parameterization $\boldsymbol{\theta}$ is treated as fixed, and the function is considered vary with respect to the configuration of atoms, \mathbf{R} . However, potential development is an inverse problem where the potential developer is looking to determine the best parameterization, $\boldsymbol{\theta}^*$, based upon a fixed set of atomic configurations, as in the force-matching method of Ercolessi and Adams[3], or are probed interdirectly through the calculation of specific material properties. As a result, the empirical potential treated as varying due to changing the parameterization, $\boldsymbol{\theta}$, while keeping the set of atomic configurations fixed \mathbf{R} . For the application of the potential development, we can rewrite Equation 3-3, where the error function is a function of the parameterization, while keeping the set of interatomic configurations fixed.

$$\epsilon(\boldsymbol{\theta} : \mathbf{R}) = V(\mathbf{R}) - \hat{V}(\boldsymbol{\theta}\mathbf{R}) \quad (3-4)$$

A more popular approach in potential developmet comes from fitting an interatomic potential so that predicted values of material properties predicted by the interatomic potential corresponds with either high-fidelity predictions done through more computationally expensive *ab initio* calculations or directly through experimental observations. The material properties calculated are referred to as a quantity of interest, q , while the predictions made by the potential denoted, \hat{q} . Since \hat{q} is ultimately detemined from energy calculations upon atomic structures, either directly or though numerical estimation, we can think of $\hat{q} : (\hat{V}(\boldsymbol{\theta}), \{\mathbf{R}_1, \dots, \mathbf{R}_N\}) \rightarrow \mathbb{R}$.

$$\epsilon(\boldsymbol{\theta} : \{\mathbf{R}_1, \dots, \mathbf{R}_N\}) = \hat{q}(\boldsymbol{\theta} : \{\mathbf{R}_1, \dots, \mathbf{R}_N\}) - q \quad (3-5)$$

3.2.1

3.3 Multi-objective optimization

Many decision and plannning problems involve multiple conflicting criteria which must be considered simultaneously. In the field of optimization, problems which have multiple criteria are deferred to as multiple critieria decision making problems (MCDM) and the algorithms used to solve them as multiple-objective optimization (MOO).

3.3.1 Loss Functions

What follows is a discussion of single objective optimization within the context of potential development before discussing multiple objective optimization before discussing multiple objective optimization we will first discuss single-objective optimization to introduce the terminology and notation used throughout the rest of this book. We To introduce the terminology used within this work, it is instructive to dispose of implementation specifics of algorithms and numerical estimation techniques, and think of an optimization problem in terms of sets. Here A is typically subset of Euclidean space \mathbf{R}^n , but could be mathematically formulated to include non-quantitative data or functionals. Then the goal of single objective optimization is to select the element $\mathbf{x}_0 \in A$, such that $F(\mathbf{x}_0) \leq F(\mathbf{x})$ for all $\mathbf{x} \in A$.

The problem of potential development can be cast as an optimization problem. L We start by casting the problem of potential development by adopting the The general multi-objective optimization (MOO) Using the notation of Marley and Arora[4], the general multi-objective optimization problem (MOO) is expressed mathematically as

$$\begin{array}{ll} \underset{\boldsymbol{\theta} \in \Theta}{\text{minimize}} & \mathbf{L}(\boldsymbol{\theta}) = [L_1(\boldsymbol{\theta}), L_2(\boldsymbol{\theta}), \dots, L_N(\boldsymbol{\theta})]^T \end{array} \quad (3-6)$$

$$\begin{array}{ll} \text{subject to} & g_j(\mathbf{x}) \leq 0, j = 1, 2, \dots, m \end{array} \quad (3-7)$$

$$h_k(\mathbf{x}) = 0, k = 1, 2, \dots, n \quad (3-8)$$

$$\mathbf{x} \in \mathbf{X} \quad (3-9)$$

where k is the number of objective functions, m is the number of inequality constraints, and e is the number of equality constraints. The vector $\mathbf{x} \in \mathbf{X} \subseteq \mathbb{R}^n$ is a vector design variables x_i , and X is feasible design space. $\mathbf{F}(\mathbf{x}) \in \mathbb{R}^k$ are called objectives, cost functions, or criteria. The feasible criterion space Z is defined as $\{\mathbf{F}(\mathbf{x}) | \mathbf{x} \in \mathbf{X}\}$.

The objective function, $F_1(\mathbf{x}) : \mathbb{R}^n \rightarrow \mathbb{R}$, For MOOs, the objectives are generally conflicting, preventing simultaneous optimization.

3.3.2 Cost function method

3.3.3 Pareto optimality

If all functions are for minimization, a feasible solution \mathbf{x}_1 is said to dominate another feasible solution \mathbf{x}_2 , denoted $\mathbf{F}(\mathbf{x}_1) \succ \mathbf{x}_2$, if and only if $F_i(\mathbf{x}_1) \leq F_i(\mathbf{x}_2)$ for $i = 1, \dots, k$ and $F_j(\mathbf{x}_1) < F_j(\mathbf{x}_2)$ for at least one objective function j . A solution is said to be Pareto optimal if it is not dominated by any other solution in the solution space.

A Pareto optimal solution cannot be improved with respect to any objective without worsening at least one objective function. The set of all feasible non-dominated solutions in X is referred to as the Pareto optimal set, and for a given Pareto optimal set, the corresponding values in the objective space are called the Pareto Front.

We can contrast this to single objective function optimization. If $\mathbf{F}(\mathbf{x}) = F(\mathbf{x})$, then this problem becomes a scalar optimization problem. The Karush-Kuhn-Tucker conditions [5, 6] are necessary to solve non-linear optimization problems. Often this is stated as the condition that $F(\mathbf{x})$ is convex with respect to the convex set \mathbf{x} , that is that the inequality constraints, $g_i(\mathbf{x})$. If $F(\mathbf{x})$ is convex with respect to the domain of \mathbf{x} , the solution can be solved with elementary multivariate calculus methods.

3.4 Application for Potential Development

At the heart of this work, the development Parameter estimation can be stated as a MOO problem. While this is occasionally stated in potential development literature, it is often within the context of the use of global optimization techniques. The purpose of this section is provide a clear methodological approach to determining the optimal parameters within the context of MOO, and elucidate the problems often encountered in potential development specifically to the choice of optimization techniques often employed in potential development.

Let $V(r_{ij}, \boldsymbol{\theta})$ be an analytical potential, dependent upon the distance, r_{ij} , between atoms i and j ; the parameters of the potential are defined by the array $\boldsymbol{\theta} = (\theta_1, \dots, \theta_P)$ for P parameters. Then to calculate material properties, the potential is combined with

the structures and the necessary simulation conditions, such as temperature, pressure, and volume. Since there is a difference between the predicted material properties which a potential predicts and the actual material properties, it is necessary to introduce notation to differentiate the two. The predicted material properties will be denoted by $\hat{\mathbf{q}} = (\hat{q}_1, \dots, \hat{q}_M)$, while the actual material property will be denoted by $\mathbf{q} = (q_1, \dots, q_M)$ for M structural properties. The notation of q comes from verification, validation, and uncertainty quantification literature where the term quantity of interest (QOI) is used.

Then for the purposes potential development, a potential can than be viewed as a function $V : \Theta \rightarrow \hat{\mathbf{Q}}$ where the parameters $\theta \in \Theta$ maps to $\hat{\mathbf{q}} \in \hat{\mathbf{Q}}$. Since $\hat{\mathbf{q}}$ is a function of the potential V , then we denote this relationship $\hat{\mathbf{q}}(\theta)$ and $\hat{\mathbf{Q}}(\theta)$.

3.4.1 Fitting Database

A fitting database is a collection of structure property functions q_i with an associated atomic configurations, also referred to as structures. The set of all possible atomic configuration is referred to as the configuration space. The goal of a fitting database to find to find a representative set of structures in which to calculate the structure property relationships q_i .

Lattice constant, bulk modulus, vacancy formation energy, or anything that can be defined from energy structures. In the fitting database, the structure proerty functions evaluated using an empirical potentials and compared to target reference values, with values either determined from experimental values or a a high-fidelity structure such as DFT. The collection of structure property relationships, is denoted $\mathbf{q} = (q_1, q_2, \dots, q_N)$ for N structure property relationships. Usually accuracy and transferability are tested against an external database.

In literature, the developers of potentials tend to use 0 K properties. A more important reason why potentials are fit to 0 K properties, is that it allows the incorporation of first-principles data. The most ubiquitous *ab initio* techniques are calculations using density functional theory (DFT). DFT allows the calculation of structural properties

which are experimentally difficult to access, as well as provide energetic information from kinetically unstable structures. The incorporation of first-principles data in the fitting database significantly improves the reliability of semi-empirical potentials by sampling a larger area of configuration space[21-28]. This is covered in detail in a review article by Payne *et al*[7].

Ercolessi F, Adams JB. Europhys Lett 1994;26:583. Mishin Y, Farkas D, Mehl MJ, Papaconstantopoulos DA. Phys Rev B 1999;59:3393 Baskes MI, Asta M, Srinivasan SG. Philos Mag A 2001;81:991 Mishin Y, Mehl MJ, Papaconstantopoulos DA, Voter AF, Kress JD. Phys Rev B 2001;63:224106 Mishin Y, Mehl MJ, Papaconstantopoulos DA. Phys Rev B 2002;65:224114 Li Y, Siegel DJ, Adams JB, Liu XY. Phys Rev B 2003;67:125101 Zope RR, Mishin Y. Phys Rev B 2003;68:024102 Mishin Y. Acta Mater 2004;52:1451

From a computational standpoint, at 0 K the calculation of material properties become precise because atomic motion stops, and only a single evaluation of a parameterization needs to be evaluated against the reference value. When the $T > 0$, issues with sampling arise. In the long time limit, the sampled trajectory yields detailed information about the Hamiltonian. Shorter trajectories yield incomplete information and confound comparison of parameters with experimental values.

When many $\hat{q}(\theta)$ has to be evaluated many times, fitting to structure property relationships which are dependent upon thermodynamic ensembles for $T > 0$ becomes quickly computational infeasible.

3.4.2 Prediction Error function

In order to assess the prediction errors of the structure property functions, we denote the $\hat{q}(\theta) = (\hat{q}_1(\theta), \hat{q}_2(\theta), \dots, \hat{q}_N(\theta))$ as the predicted material properties

The difference between the prediction values and target values of the QOIs produces a vector of error functions, $\epsilon(\theta) = (\hat{q}_1(\theta) - q_1, \hat{q}_2(\theta) - q_2, \dots, \hat{q}_N(\theta) - q_N)$,

3.4.3 Parameters

Let V be an empirical potential parameterized by P number of parameters $\boldsymbol{\theta} = [\theta_1, \theta_2, \dots, \theta_P]$.

3.4.4 Constraints on parameters

3.4.5 Structure Property Relationships

3.4.6 Constraints on structure property relationships

3.4.7 Parameter Optimization Problem as MOO formulation

DEFINITION OF CONFIGURATION SPACE

3.5 Pareto Front

In multiobjective optimization problems, it is characteristic that no unique solution exists, but a set of mathematically equally good solutions can be identified. These solutions are known as nondominated, efficient, noninferior or Pareto optimal solutions. In MCDM literature, these terms are synonymous.

In MCDM literature, the idea of solving a multiobjective optimization problem is understood as helping a human decision maker (DM) in understanding the multiple objectives simultaneously and finding a Pareto optimal solution. Thus, the solution process requires some interaction with the DM in the form of specifying preference information and the final solution is determined by these preferences.

In potential development, the preferences of potential developer likewise influences are particular parameterization, which has results in the development of empirical potentials as somewhat of a black art. In the end, empirical potentials are simplified models which predict structure property relationships.

In classical potential optimization, the identification of an optimal parameterization is determined by the minimization of a cost function which couples multiple objective functions, usually a weighted sum of squares, and different weights are used in an interactive fashion until an acceptable parameterization is determined.

3.6 Surveys of Methods

Chankong and Haimes 1983 Hwang and Masud 1979 Marler and Arora 2004
Miettinen 1999 Sawaragi et al 1985 Steuer 1987 Vincke 1992

We start our review of methods using Hwang and Masud 1979 and Miettinen 199, to classify the different classes of approaches by methodological approach rather than technical techniques.

3.6.1 no preference methods

The task is to find some neutral compromise solution without any additional information. This means instead of asking the DM for preference information, some assumption are made about what a reasonable compromise could be like.

3.6.2 *a priori* methods

In *a priori*, the DM first articulates preference information and the solution tries to find a Pareto optimal solution satisfying them as well as possible.

3.6.3 *a posteriori* methods

A representation of a set of Pareto optimal solution is first generated and then the DM is supposed to select the most preferred one among them. This approach gives the DM an overview of different solutions available but if there are more than two objectives in the problem, it may be difficult for the DM to analyze the large amount of information.

3.6.4 Interactive methods

After each iteration, some information is provided to the DM in order to specify preference information. What is noteworthy is that the DM can specify and adjust one's preferences between each iteration and at the same time learn about interdependencies between each iteration and at the same time learn about interdependencies in the problem as well as one's own preferences.

3.7 Solution Methods

MOO solution methods fall under the category of scalarization or non-scalarization methods. Scalarization is the primary method for MOO problems [Miettinen 1999].

Scalarization converts the MOO problem into a parameterized single-objective problem which can be solved using well-established single-objective optimization methods.

3.7.1 Scalarization Methods

3.7.1.1 Weighting Method

3.7.2 Cost Function

$$C(\boldsymbol{\theta}) = \sum w_i (\hat{q}_i(\boldsymbol{\theta}) - q_i)^2 \quad (3-10)$$

Gass and Saaty 1955 Zadeh 1963

For an interatomic potential being fit with respect to k quantities of interest,

$$\begin{aligned} & \underset{\boldsymbol{\theta}}{\text{minimize}} && \sum_{i=1}^k w_i \varepsilon_i^2(\boldsymbol{\theta}) \\ & \text{subject to} && \boldsymbol{\theta} \in \Theta \end{aligned} \quad (3-11)$$

where $w_i \geq 0$ for $i = 1, \dots, k$ Weakly Pareto optimal.

In the development of interatomic potentials, the DM is asked to specify weights in which case the method is used as an *a priori* method.

Algorithms for multiobjective optimization should produce Pareto optimal solutions, and that any Pareto optimal solution can be found. Censor1977 discusses the conditions which the whole Pareto set can be generated by the weighting method when positive weights are presented. In this respect, the weighting method has a serious shortcoming. Any Pareto optimal solution can be found by altering weights only if the problem is convex. Some Pareto optimal solutions of nonconvex problems cannot be found regardless of how the weights are selected.

The problems of the weighting schemes have been explored by the classical potential development community. The method may jump from one vertex to another vertex leaving intermediate solutions undetected with relatively small changes in the weighting schemes.

Scaling of the objective functions.

The weighting method can be used as an *a posteriori* method where different weight can be used to generate different Pareto optimal solutions, and then the DM selects the most satisfactory solution. Systemic methods of perturbing the weights to obtain different Pareto optimal solutions are suggested (Chankong and Haimes 1983), but Das and Dennis 1997 illustrates that an evenly distributed set of weights does not necessarily produce an evenly distributed representation of the Pareto optimal set, even when the problem is convex.

When the weighting scheme is used as an *a priori* method, the DM is expected to represent his/her preferences in the form of weights. Roy and Mousseau (1996) suggests that the role of weights in expressing preferences maybe misleading. Although the relative importance of weights show the relative importance of the objective functions it is not clear what underlies this notion. The relative importance of objective functions is usually understood globally, for the entire decision problem, while many practical applications show that the importance typically varies for different objective function values, that is, the concept is only meaningful locally. (Podinovsky 1994).

Weights that produce a certain Pareto optimal solution are not necessarily unique, and different weights may produce similar solutions. On the other hand, a small change in weights may cause big differences in the objective function. It is not easy for the potential developer to control the solution process because weights behave in an indirect way. The solution process then becomes an interactive one where the DM tries to guess such weights that would produce a satisfactory solution, and this is not desirable because the DM cannot be properly supported which leads to frustration complications in potential development. Instead, in such cases it is advisable to use real interactive methods where the DM can better control the solution process with more intuitive preference information.

The weighting method is also difficult

3.8 Optimization Methods

$$\begin{aligned} & \underset{x}{\text{minimize}} && f(x) \\ & \text{subject to} && g_i(x) \leq 0 \quad h_j(x) = 0 \quad x \in X \end{aligned} \tag{3-12}$$

here x is the optimization variable, f is the objective function, g_i are inequality constraints, and h_j are equality constraint functions.

3.8.1 Convex Optimization

Numerical algorithms make heavy use of scalarization results, and most papers in the field of MOO and economics deal with non-linear programming problems, corresponding duality theorems, and the repeated application of the simplex method.

However, within the literature of potential development approaches focus upon local minimization techniques and global optimization techniques.

objective function is concave. constraint set is convex. KKT requirements for uniqueness.

3.8.2 Global Approaches

Genetic algorithms are a popular meta-heuristic that is particularly well-suited for this class of problems. Traditional GA are customized to accomodate multi-objective problems by using specialized fitness functions and introducing methods to promote solution diversity.

The second general approach is to determine an entire Pareto optimal solution set or a representative subset. A Pareto optimal set is a set of solutions that are nondominated with respect to each other. While moving from one Pareto solution to another, there is always a certain amount of sacrifice in one objective(s) to achieve a certain amount of gain in the other(s). Pareto optimal solution sets are often preferred to single solutions because they can be practical when considering real-life problems since the final solution of the decision-maker is always a trade-off. Pareto optimal sets can be of varied sizes, but the size of the Pareto set usually increases with the increase in the number of objectives.

The ultimate goal of a multi-objective optimization algorithm is to identify solution in the Pareto optimal set. However, identifying the entire Pareto optimal set, for multi-objective problems, is impossible to its size. Proof of solution optimality is computationally infeasible. Therefore, a practical approach is achieve successively better approximations of the Pareto surface that represent the Pareto set as well as possible.

A multi-objective optimization approach should achieve the following conflicting goals as described by Zitzler *et al*[8]: (1) the best known Pareto front should be as close as possible to the true Pareto front. Ideally, the best-known Pareto set should be a subset of the Pareto set, (2) solutions in the best known Pareto set should be uniformly distributed and diverse over the Pareto front in order to provide the decision-maker a true picture of trade-offs, and (3) the best-known Pareto front should capture the whole spectrum of the Pareto front at the extreme ends of the spectrum. While the first two goals are important for multi-objective optimization, the last goal is erroneous. In general, when developing potentials, the DM is interested in compromise solutions and a parameterization with high fidelity with respect to one material property at the expense of a loss of fidelity with respect to all other prediction would be a pathological parameterization.

3.8.2.1 Genetic Algorithms

The method which will be proposed in chapter 5 is not a genetic algorithm, but has many similarities as Genetic Algorithms but tailored to create an ensemble of Pareto optimal parameters. However, it is a genetic solution and the iterative approach of generating new populations is akin to previous solutions. As a result, the section of review in this section is necessarily incomplete but refer to an introductory review by Konak *et al*[9] as well as the book by Deb[10]

The concept of genetic algorithms were inspired by evolutionist theories explaining the origin of species[11]. In nature, weak and unfit speices within their environment are faced with extinction by natural selection, while strong ones pass on their genes to

future generations through reproduction. In the long run, species carrying the correct combination in their genes become dominant in their population.

In GA terminology, a solution vector $\mathbf{x} \in \mathbf{X}$ is called an individual or a chromosome. Chromosomes are made of discrete units called genes. Each gene controls one or more features of the chromosome. Normally, a chromosome corresponds to a unique solution \mathbf{x} in the solution space. This requires a mapping mechanism between the solution space and chromosome. GA operates with a collection of chromosomes, called a population. As the search evolves, the population includes fitter and fitter positions, eventually it converges, meaning that it is dominated by a single solution. Two operators are defined crossover and mutation. In the crossover operator, two parent solutions are combined together to form offspring. The mutation operator introduces random changes into the population.

The first multi-objective GA, called vector evaluated GA (or VEGA), was proposed by Schaffer [5]. Afterwards, several multi-objective evolutionary algorithms were developed including Multi-objective Genetic Algorithm (MOGA) [6], Niched Pareto Genetic Algorithm (NPGA) [7], Weight-based Genetic Algorithm (WBGA) [8], Random Weighted Genetic Algorithm (RWGA) [9], Nondominated Sorting Genetic Algorithm (NSGA) [10], Strength Pareto Evolutionary Algorithm (SPEA) [11], improved SPEA (SPEA2) [12], Pareto-Archived Evolution Strategy (PAES) [13], Pareto Envelope-based Selection Algorithm (PESA) [14], Region-based Selection in Evolutionary Multiobjective Optimization (PESA-II) [15], Fast Non-dominated Sorting Genetic Algorithm (NSGA-II) [16], Multi-objective Evolutionary Algorithm (MEA) [17], Micro-GA [18], Rank-Density Based Genetic Algorithm (RDGA) [19], and Dynamic Multi-objective Evolutionary Algorithm (DMOEA) [20]. Note that although there are many variations of multi-objective GA in the literature, these cited GA are well-known and credible algorithms that have been used in many applications and their performances were tested in several comparative studies.

Vector Evaluated Genetic Algorithm (VEGA). Schaffer proposed VEGA for finding multiple solutions to multiobjective problems. He created VEGA to find and maintain multiple classification rules in a set covering problem. VEGA tried to achieve this goal by selecting a fraction of the next generation using one of the objective functions.

Fitness Sharing encourage the search in unexplored section of a Pareto front by artificially thinning solutions in densely populated area. To achieve this goal, densely populated areas are identified and a penalty method is used to penalize the solutions located in such areas. This approach was recommended by Goldberg and Richardson[12] and used by Fonseca and Fleming[13] to penalize clustered solutions.

$$dz(\mathbf{x}_1, \mathbf{x}_2) = \sqrt{\sum_{k=1}^K \left(\frac{z_k(\mathbf{x}_1) - z_k(\mathbf{x}_2)}{z_k^{max} - z_k^{min}} \right)^2} \quad (3-13)$$

based on these distances, calculate a niche count for each solution $\mathbf{x} \in \mathbf{X}$ as

$$nc(\mathbf{x}_1, t) = \sum_{\mathbf{x}_2 \in \mathbf{X}, r(\mathbf{x}_2, t) = r(\mathbf{x}_1, t)} \max \left\{ \frac{\sigma_{share} - dz(\mathbf{x}_1, \mathbf{x}_2)}{\sigma_{share}}, 0 \right\} \quad (3-14)$$

where σ_{share} is the niche size by defining a neighborhood of solutions in the objective space. Solutions in the same neighborhood contribute to each other's nich count.

Therefore, a solution in a crowded neighborhood will have a higher niche count, reducing the probability of selecting that solution from being culled from the survivor set.

3.9 Visualization

This problem is dealt with in discussions about visualization and and analysis of the large amounts of data generated from a posteriori approaches to solving these problems.

Edgeworth 1881 Koopmans 1951 Kuhn Tucker 1951 Pareto 1896, 1906

3.10 Treatment

Our treatment of the mapping of the empirical potential is treated as a bijective mapping into two measure spaces.

Let us define parameter space with the probability measure space $(\Theta, \mathcal{F}(\Theta), \mathbb{P})$.

Then we define the error space of the structure property relationships with the probability measure space $(\mathcal{E}, \mathcal{F}(\mathcal{E}), \mathbb{Q})$.

To solve forward problems, the parameters of a potential, $\boldsymbol{\theta}$ is known *a priori*, are used in conjunction of a set of atomic arrangements in a simulation cell with periodic boundary conditions to predict n material properties, $\mathbf{q} = (q_1, \dots, q_n)$. These predictions depend not only on the atomic arrangements but also on the parameterization, denoted $\hat{\mathbf{q}}(\boldsymbol{\theta}) = (\hat{q}_1(\boldsymbol{\theta}), \dots, \hat{q}_n(\boldsymbol{\theta}))$. The differences between the predicted values and references values are denoted $\boldsymbol{\epsilon}(\boldsymbol{\theta}) = |\hat{\mathbf{q}}(\boldsymbol{\theta}) - \mathbf{q}|$, where $|\mathbf{x}|$ is the elementwise magnitude of the vector \mathbf{x} .

The problem of parameterization is an inverse problem where an optimal parameterization produces ideal outcomes for the forward problem, i.e. difference between the predicted value and the reference value, $\epsilon_i(\boldsymbol{\theta}) = 0$. Since replication of results is typically not achievable, then the goal of parameterization becomes $\min_{\boldsymbol{\theta}} \epsilon_i(\boldsymbol{\theta})$ for all i . Typically, there does not exist an optimal parameterization, $\boldsymbol{\theta}^*$, which minimizes $\epsilon_i(\boldsymbol{\theta})$ for all $i < n$. Requiring a prioritization of which material properties have a preference for fidelity in predictions.

The typical approach to solving the inverse problem transforms the above problem into a scalar optimization problem amenable to derivative approaches. A cost function C which couples the individual objectives, ϵ_i , along with a set of weights $\mathbf{w} = (w_1, \dots, w_n)$, to represent preferences, that is

$$C(\boldsymbol{\theta}) = \sum_i^n w_i (\hat{q}_i(\boldsymbol{\theta}) - q_i)^2 = \sum_i^n w_i \epsilon_i^2(\boldsymbol{\theta}) \quad (3-15)$$

It is clear that the selection of \mathbf{w} uniquely determines $\boldsymbol{\theta}^*$. However, the values of w_i which will produce an acceptable potential are typically not known *a priori*. When the initial weighting scheme fails to give an acceptable results, \mathbf{w} is changed in an *ad hoc* approach until an acceptable parameterization is achieved.

Since analytical solutions are intractable, numerical solutions are achieved by selecting an initial parameterization, $\boldsymbol{\theta}_0$, and using derivative-based optimization techniques to minimize the cost function. If the $C(\boldsymbol{\theta})$

We generalize the problem of parameter estimation by casting it more generally into a multi-objective optimization problem:

$$\min_{\boldsymbol{\theta}} \boldsymbol{\epsilon}(\boldsymbol{\theta}) = \begin{bmatrix} \epsilon_1(\boldsymbol{\theta}) \\ \vdots \\ \epsilon_n(\boldsymbol{\theta}) \end{bmatrix} = \begin{bmatrix} \hat{q}_1(\boldsymbol{\theta}) - q_1 \\ \vdots \\ \hat{q}_n(\boldsymbol{\theta}) - q_n \end{bmatrix} \quad (3-16)$$

To remove the dependence on *a priori* performance preferences, it is necessary to define an ensemble of parameterizations which are optimal in a sense. Suppose we have two parameterizations, where $\boldsymbol{\theta}_1$ dominates $\boldsymbol{\theta}_2$, denoted $\boldsymbol{\theta}_1 \prec \boldsymbol{\theta}_2$, when $\epsilon_i(\boldsymbol{\theta}_1) \leq \epsilon_i(\boldsymbol{\theta}_2) \forall i \in \{1, \dots, n\}$ and $\exists i \in \{1, \dots, n\}, \epsilon_i(\boldsymbol{\theta}_1) < \epsilon_i(\boldsymbol{\theta}_2)$. We say that $\boldsymbol{\theta}_n$ is Pareto efficient if $\nexists \boldsymbol{\theta}_i \in \Theta, \boldsymbol{\theta}_i \prec \boldsymbol{\theta}_1$.

The Pareto set $\Theta^{(p)}$ is the set of all Pareto efficient points, that is the set of nondominated points. While performance requirements have not yet been encoded to determine $\boldsymbol{\theta}^*$, this point must fall in the Pareto set, $\boldsymbol{\theta}^* \in \Theta$. If ϵ_i are competing, then clearly there are parameterizations which performs well with respect to ϵ_i , but poorly with respect to ϵ_j .

We originally defined Θ as a compact space of the parameters $\boldsymbol{\theta}$ defining the feasible θ -space. In a deterministic approach we would want to identify an algorithm such that we start with feasible set of parameterizations and constrains the sets of parameterizations until it produces a set of parameterizations which produces the Pareto set in ϵ -space, that is a process

$$\Theta = \Theta_0 \supset \Theta_1 \supset \dots \supset \Theta_k = \Theta^{(p)} \quad (3-17)$$

which produces due to Eq ?? and ??

$$\mathcal{E} = \mathcal{E}_0 \subset \mathcal{E}_1 \supset \dots \supset \mathcal{E}_k = \mathcal{E}^{(p)} \quad (3-18)$$

for $k < \infty$ iterations. Since $\Theta \subset \mathbb{R}^p$ and $\mathcal{E} \subset \mathbb{R}^n$, we provide the following approach which uses Monte Carlo simulation in an approach which is inspired by Bayesian inference, although this approach does not use a Bayesian updating approach. The goal of this approach is to produce an ensemble of $\boldsymbol{\theta} \in \Theta^{(p)}$ and describe this ensemble as a probability distribution which could be used as a starting point in uncertainty quantification propagation.

We propose the following approach:

$$\Theta_k \rightarrow \hat{Q}_k(\Theta_k) \rightarrow \mathcal{E}_k(\Theta_k) \quad (3-19a)$$

$$\mathcal{E}_k(\Theta_k) \rightarrow \mathcal{E}_k^{(p)}(\Theta_k^{(p)}) \quad (3-19b)$$

$$\mathcal{E}_k^{(p)}(\Theta_k^{(p)}) \rightarrow \mathcal{E}_k^{(cp)}(\Theta_k^{(cp)}) \quad (3-19c)$$

$$\mathcal{E}_k^{(cp)}(\Theta_k^{(cp)}) \rightarrow \Theta_{k+1} \quad (3-19d)$$

The notation $\rho(\boldsymbol{\theta})$ refers to the joint probability density function that $\boldsymbol{\theta} \in \Theta^P$. Intuitively, one can think of $\rho(\boldsymbol{\theta})\Delta\boldsymbol{\theta}$ as the probability that a random variable drawn from $\rho(\boldsymbol{\theta})$ will fall within the infinitesimal compact set $[\boldsymbol{\theta}, \boldsymbol{\theta} + \Delta\boldsymbol{\theta}]$

Even if Θ is defined as compact, \hat{Q} may not be bounded. By construction $\hat{q}_i > 0$, however \hat{q}_i may not be bounded from above. There exists $\boldsymbol{\theta} \in \Theta$ which produces pathological members of the Pareto set. Specifically, there is exists $\boldsymbol{\theta} \in \Theta$ such that $\boldsymbol{\epsilon}(\boldsymbol{\theta}) \in \mathcal{E}(p)$, but produces an $\epsilon_i(\boldsymbol{\theta}) > \epsilon_{i,max}$ for at least one $i \in \{1, \dots, n\}$, where $\epsilon_{i,max}$ is an arbitrary performance requirement.

We generalize Eq To estimate $\Theta^{(p)}$, we simplify the drawing of samples from a uniform distribution defined by hyperrectangles which defines Θ The choice of

3.10.0.1 Kernel Density Estimate

The Kullback-Leiber divergence[14] measures the divergence between two probability density functions $f(x)$ and $g(x)$,

$$D(f \parallel g) = \int f(x) \log \frac{f(x)}{g(x)} dx \quad (3-20)$$

is commonly used in statistics as a measure of similarity between two density distributions, and has the following properties: (1) self-similarity, $D(f \parallel f) = 0$, (2) self-identification, $D(f \parallel g) = 0$ only if $f = g$, and (3) positivity, $D(f \parallel g) \geq 0$ for all f and g .

The integral in Equation 3-20 can be calculated from Monte Carlo[15], by drawing a sample x_i , from the statistical distribution of f such that $\mathbb{E} \left[\log \frac{f(x)}{g(x)} \right] = D(f \parallel g)$. Using N i.i.d. samples $\{x_i\}_{i=1}^N$, we have

$$D_{MC}(f \parallel g) = \frac{1}{N} \sum_i^N \log \frac{f(x)}{g(x)} \rightarrow D(f \parallel g) \quad (3-21)$$

as $n \rightarrow \infty$. The variance of the estimation error is $\frac{1}{N} \text{Var}_f \left[\log \frac{f}{g} \right]$. To compute $D_{MC}(f \parallel g)$, we need to generate samples $\{x_i\}_{i=1}^N$ from f . Then for $1 \leq i \leq N$, evaluate $f(x_i)$ and $g(x_i)$ to calculate D_{MC} .

3.11 Methodology

To demonstrate the potential of this process to develop a working potential, a Coulumb-Buckingham potential[16] is developed for magnesium oxide (MgO). This pair wise potential for atoms i and j

$$V(r_{ij}; A, \rho, C) = \frac{Z_i Z_j}{4\pi\epsilon_0 r_{ij}} + A \exp\left(-\frac{r_{ij}}{\rho}\right) - \frac{C}{r_{ij}^6} \quad (3-22)$$

where $r_{ij} = \|\mathbf{r}_i - \mathbf{r}_j\|_2$ is the distance between the atoms i and j , and q_i and q_j describe the charges of the atoms, and A , B , and C , are the parameters of the potential.

The first term of the potential is the electrostatic potential energy, the second term is repulsive due to the Pauli exclusion principle, and the third term is an attractive van der Waals energy.

We use the same relevant assumptions used in Lewis and Catlow[16], the Mg-Mg interactions are assumed to be purely coulombic, the Mg-O is considered to be the Born-Mayer form, $A \exp(-r/\rho)$, where the van der Waals term is ignored.

The charge of the atoms is allowed to deviate from their formal charges, provided that $Z_{Mg} = -Z_O$, to preserve charge neutrality.

3.11.1 Reference Values

3.11.2 Implementation

Implemented in Python using LAMMPS as the molecular dynamics engine as the calculator. Parrellization is done through MPI.

CHAPTER 4

APPLICATIONS TO IONIC SYSTEMS

Lewis Catlow potential[17]

Henkelman *et al*[18]

Lewis and Catlow[17] parameterized a wide range of oxide systems with a pairwise potential, between two atoms i and j .

$$V_{ij}(r_{ij}) = \frac{Z_i Z_j}{r_{ij}} + A_{ij} \exp(-r_{ij}/\rho_{ij}) - \frac{C_{ij}}{r_{ij}^6} \quad (4-1)$$

The physics of ionic systems is modelled with three pairwise terms. The first term is a Coulombic interaction dependent on the the point charges, Z_i and Z_j . The other terms is a Buckingham potential the repulsion between the two ions due to the Pauli exclusion principle with the exponential function combined with a term for a weak van der Waals interaction. In the Lewis and Catlow parameterization (LC), the charges are assumed to have the formal charges of $\pm 2e$ on the magnesium and oxygen ions, respectively. Additionally, the cations only interact with each other though the Coulomb interaction.

Two potentials unpublished Buckingham potentials were developed by Ball and Grimes (BG1 and BG2), but were used in the work of Henkelman *et al*[18].

CHAPTER 5

APPLICATIONS TO NICKEL EMBEDDED ATOM POTENTIALS

The aim of this chapter is to apply the earlier described methods and tools involved in developing potentials for metallic systems. The defining difference between metals and nonmetals is the lack of an energy gap between ground and excited states. Metallic systems are normally characterized as a system existing within a sea of delocalized electrons.

5.1 Insights from Quantum Mechanical Techniques

In the development of the Finnis-Sinclair method, the second-moment tight-binding(3)

5.2 Embedded Atom Model

For metallic systems, the most common potential forms are those of the Finnis-Sinclair method[19] and the embedded atom model (EAM) [20, 21]. Both of these approaches have similar formalisms which combine a pair-potential function and an energy functional dependent upon the electron density contributions from an atoms neighbors with the total energy of the system V being described as

$$V = \sum_{i < j} \phi_{s_i s_j}(r_{ij}) + \sum_i F_{s_i}(\bar{\rho}_i) \quad (5-1)$$

The first term is the summation over all neighbors of a pair potential of a pair potential energy(ϕ_{ij}) between two atoms, i and j , with the chemical species, s_i and s_j . The second term is the embedding energy (F_i) necessary to place the atom i at its position in an electron gas density ($\bar{\phi}_i$) influenced by all the neighbors of the atom. In EAM, the host electron density is given by the sum of the contributions ρ_i is represented by the sum of the contributions $\rho_{s_j}(r)$ from all neighboring atoms j .

$$\bar{\rho}_i = \sum_{j \neq i} \rho_{s_j}(r_{ij}) \quad (5-2)$$

In the Finnis-Sinclair potential, $F_{s_i}(\bar{\rho}) = -\sqrt{(\bar{\rho}_i)}$

5.3 Approaches to EAM Potential Development

The original formulation of the EAM represented the reepulsion between the atomic cores (nuclei and inner electron shells), represented by a power law or an Born-Mayer type exponential function. In these cases, the pair potential, ϕ , is purely repulsive, while the embedding energy F was attractive. Later EAM pair potentials used Morse Functions[10,19,20], which has a distinct energy well, while the embedding function in these cases serves as a corrective term.

In either case, the electron density function and the pair potential are given as analytic functions of the radial separation of two atoms r_{ij} with fitted parameters. The embedding function is sometimes specified as having a specific functional form, or determined by fitting the embedding function to an equation of state such as Rose *et al*[21].

For Nickel, Johnson and Oh[22], Voter-Chen[19,23], Angelo *et al*[20] have used parametric functional forms, where Ercolessi and Adams[24] and Mishin 25 implemented cubic-spline approaches, which do not specify an analytical functional form.

In early potential development, the parameters are adjusted to match properties such cohesive energy, lattice parameters, elastic properties, and vacancy formation energies. With additional computational power, stacking fault energies, phase order differences, and surface energies to fit to important relevant environments thought to be important to produce transferrable potentials.

5.4 Development of an EAM potential

Even when a potential has an analytical functional form. EAM potentials are specified in a functional form which is dependent a specific code format which precalculates evaluation of the $\phi(r_{ij})$, $\rho(r_{ij})$, and $F(\bar{\rho})$. Specifics of this calculation are provided in Appendix ??.

5.5 Cutoff function

5.6 Generalized Stacking Fault in FCC

The generalized stacking fault in FCC metals describe the the slip of $\{111\}$ planes of the face centered cubic cell in the $\langle 112 \rangle$ direction, which represents the energy In the early works of Frenkel and Mackenzie describe this motion as a function of the macroscopically measured shear modulus, the Burgers vector and the interplanar spacing of the $\{111\}$ planes.

Rice[3] unstable stacking faults and stable stacking faults

Vitek[23, 24] develops the notion of the generalized stacking fault, which cannot be measured experimental except at a single point knows as the intrinsic stacking fault γ_{ISF}

Calculation of unstable stacking faults[25–27] was done with EAM potentials, while DFT has been used for the calcualtion of the GSF curve [14,15,16]

Zimmerman takes the approach of creating a simulation of the FCC crystal oriented in the $\langle 111 \rangle$ direction, with the basal plane formed by the $\langle 112 \rangle$ and the $\langle 111 \rangle$ direction. For the ease of creating the stacking fault, the $\langle 112 \rangle$ direction is chosen on the x-axis, and the $\langle 110 \rangle$ is chosen for the y-axis, and the z-axis on the $\langle 111 \rangle$. To create the stacking fault, the lower half remains fixed, while the upperhalf is displaced in the $\langle 112 \rangle$ direction in small increments. Zimmerman uses 6000 atoms consisting of 30 111 planes. After lateral displacement, the atoms are allowed to relax laterally (in the $\langle 111 \rangle$ direction) except for three 111 planes at the top and bottom. This method is used in [11-13]

To create a surrogate model, we use the atomic simulation enviornment (ASE)

5.6.1 Density Functional Theory

5.6.2 Molecular Dynamics

First generate a simulation cell of a representative fcc bulk with $[1\ 1\ 2]$ in the x direction, $[\bar{1}\ 1\ 0]$ in the y direction, and $[\bar{1}\ \bar{1}\ 1]$ in the z-direction, which was adapted from the script of Spear[28].

Calculation of Point Defect Energies

This appendix documents the heuristics and algorithms for the automation for the calculation of point defects. In theory, point defect calculations are dependent upon the interatomic cutoff of the interatomic potential. However, the energies of pair-wise interactions vanish quickly due to tails of power-law and exponential distribution functions. The author has found it instructive that even when the targets of the fitting database are taken from literature, *ab initio* calculations to understand how large the size that the representative volume should be to prevent defect interaction

.1 Calculation of Point Defects

In ionic materials, the formation of energy of a defect d with charge q is calculated as

$$E_d^f = E_{def} - E_{perf} = \sum_{\alpha} n_{\alpha} \mu_{\alpha} - q \mu_e + E_{chcor} + E_{elcor} \quad (3)$$

A point defect occur at or around a lattice point, there are not expanded into space in any direction.

A vacancy are lattice sites which would be occupied in a single crystal, but are vacant. The stability of surrounding crystal structure prevents the atoms from occupying the vacancy.

In an ionic solid, the combination of a two vacancies of a cation and anion species are referred to as a Schottky defect, which is neutral in nature.

.2 Creation of Supercell

The technique for creating supercell

.2.1 Definition of the defect in supercell calculation

.2.2 Convergence conditions

To ensure that convergence

.3 Future Work

.4 Robustness of Potentials

Sensitive analysis. Many models use cutoff-radii as an additional parameter to be determined by the fitting process. Because of the nature of the stacking fault, the GSF energy must depend upon non-nearest neighbor interactions. However, a slight alteration of the cutoff-radius was found to have a dramatic impact on the behavior of EAM potentials by Zimmerman. He suggests that parameterized models should be only slightly sensitive to a change of value for any of its parameters. High sensitivity indicates the possibility of unphysical behavior of a model. This issue should be addressed when creating a potential to be used in simulations that involve stacking faults.

REFERENCES

- [1] M. Born and R. Oppenheimer, “Zur quantentheorie der molekeln,” *Annalen der Physik*, vol. 389, no. 20, pp. 457–484, 1927. [Online]. Available: <https://onlinelibrary.wiley.com/doi/abs/10.1002/andp.19273892002>
- [2] P. Hohenberg and W. Kohn, “Inhomogeneous electron gas,” *Phys. Rev.*, vol. 136, pp. B864–B871, Nov 1964. [Online]. Available: <https://link.aps.org/doi/10.1103/PhysRev.136.B864>
- [3] F. Ercolessi and J. B. Adams, “Interatomic potentials from first-principles calculations: the force-matching method,” *EPL (Europhysics Letters)*, vol. 26, no. 8, p. 583, 1994.
- [4] R. Marler and J. Arora, “Survey of multi-objective optimization methods for engineering,” *Structural and Multidisciplinary Optimization*, vol. 26, no. 6, pp. 369–395, Apr 2004. [Online]. Available: <https://doi.org/10.1007/s00158-003-0368-6>
- [5] W. Karush, “Minima of functions of several variables with inequalities as side constraints,” Master’s thesis, University of Chicago, 1939.
- [6] H. W. Kuhn and A. W. Tucker, “Nonlinear programming,” in *Proceedings of the Second Berkeley Symposium on Mathematical Statistics and Probability*. Berkeley, Calif.: University of California Press, 1951, pp. 481–492.
- [7] M. C. Payne, I. J. Robertson, D. Thomson, and V. Heine, “Ab initio databases for fitting and testing interatomic potentials,” *Philosophical Magazine B*, vol. 73, no. 1, pp. 191–199, 1996. [Online]. Available: <https://doi.org/10.1080/13642819608239124>
- [8] E. Zitzler, K. Deb, and L. Thiele, “Comparison of multiobjective evolutionary algorithms: Empirical results,” *Evolutionary computation*, vol. 8, no. 2, pp. 173–195, 2000.
- [9] A. Konak, D. W. Coit, and A. E. Smith, “Multi-objective optimization using genetic algorithms: A tutorial,” *Reliability Engineering & System Safety*, vol. 91, no. 9, pp. 992–1007, 2006.
- [10] K. Deb, *Multi-objective optimization using evolutionary algorithms*. John Wiley & Sons, 2001, vol. 16.
- [11] J. H. Holland, *Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence*. Ann Arbor: University of Michigan Press, 1975.
- [12] D. E. Goldberg, J. Richardson *et al.*, “Genetic algorithms with sharing for multimodal function optimization,” in *Genetic algorithms and their applications: Proceedings of the Second International Conference on Genetic Algorithms*. Hillsdale, NJ: Lawrence Erlbaum, 1987, pp. 41–49.

- [13] C. M. Fonseca and P. J. Fleming, "Multiobjective genetic algorithms," in *Genetic algorithms for control systems engineering, IEE colloquium on*. IET, 1993, pp. 6–1.
- [14] S. Kullback and R. A. Leibler, "On information and sufficiency," *Ann. Math. Statist.*, vol. 22, no. 1, pp. 79–86, 03 1951. [Online]. Available: <https://doi.org/10.1214/aoms/1177729694>
- [15] J. R. Hershey and P. A. Olsen, "Approximating the kullback leibler divergence between gaussian mixture models," in *2007 IEEE International Conference on Acoustics, Speech and Signal Processing - ICASSP '07*, vol. 4, April 2007, pp. IV–317–IV–320.
- [16] G. V. Lewis and C. R. A. Catlow, "Potential models for ionic oxides," *Journal of Physics C: Solid State Physics*, vol. 18, no. 6, p. 1149, 1985. [Online]. Available: <http://stacks.iop.org/0022-3719/18/i=6/a=010>
- [17] G. Lewis and C. Catlow, "Potential models for ionic oxides," *Journal of Physics C: Solid State Physics*, vol. 18, no. 6, p. 1149, 1985.
- [18] G. Henkelman, B. P. Uberuaga, D. J. Harris, J. H. Harding, and N. L. Allan, "Mgo addimer diffusion on mgo (100): a comparison of ab initio and empirical models," *Physical Review B*, vol. 72, no. 11, p. 115437, 2005.
- [19] M. Finnis and J. Sinclair, "A simple empirical n-body potential for transition metals," *Philosophical Magazine A*, vol. 50, no. 1, pp. 45–55, 1984.
- [20] M. S. Daw and M. I. Baskes, "Semiempirical, quantum mechanical calculation of hydrogen embrittlement in metals," *Physical review letters*, vol. 50, no. 17, p. 1285, 1983.
- [21] —, "Embedded-atom method: Derivation and application to impurities, surfaces, and other defects in metals," *Physical Review B*, vol. 29, no. 12, p. 6443, 1984.
- [22] R. Johnson and D. Oh, "Analytic embedded atom method model for bcc metals," *Journal of Materials Research*, vol. 4, no. 5, pp. 1195–1201, 1989.
- [23] V. Vitek, "Thermally activated motion of screw dislocations in bcc metals," *physica status solidi (b)*, vol. 18, no. 2, pp. 687–701, 1966.
- [24] —, "Intrinsic stacking faults in body-centred cubic crystals," *Philosophical Magazine*, vol. 18, no. 154, pp. 773–786, 1968.
- [25] Y. Sun, J. R. Rice, and L. Truskinovsky, "Dislocation nucleation versus cleavage in ni 3 ai and ni," *MRS Online Proceedings Library Archive*, vol. 213, 1990.
- [26] Y. Sun, G. E. Beltz, and J. R. Rice, "Estimates from atomic models of tension-shear coupling in dislocation nucleation from a crack tip," *Materials Science and Engineering: A*, vol. 170, no. 1-2, pp. 67–85, 1993.

- [27] D. Farkas, S. Zhou, C. Vailhe, B. Mutasa, and J. Panova, “Embedded atom calculations of unstable stacking fault energies and surface energies in intermetallics,” *Journal of materials research*, vol. 12, no. 1, pp. 93–99, 1997.
- [28] P. Spear. Lammps stacking fault energy. [Online]. Available: https://icme.hpc.msstate.edu/mediawiki/index.php/LAMMPS_Stacking_Fault_Energy

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