

# Considerations when comparing molecular dynamics simulation engines: lessons learned in the automated conversion of input files for SAMPL5

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**Abstract** We describe the efforts to prepare common starting structures and models for the SAMPL5 blind prediction challenge. We generated the starting input files and single configuration potential energies for the host-guest and distribution coefficient molecules in the SAMPL5 blind prediction challenge for the GROMACS, AMBER, LAMMPS, DESMOND and CHARMM molecular simulation programs. All conversions were fully automated from the originally prepared AMBER input files using a combination of the ParmEd and InterMol conversion programs.

We find that all programs agree to a large extent when reasonable choices are made for different cutoff parameters, though some surprising sources of sta-

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tistically significant differences occur. For example, differing choices of Coulomb's constant in each program is one of the largest sources of discrepancies in energies between the programs. We discuss the measures required to get good agreement in the energies for equivalent starting configurations between the simulation programs, and the energy differences that occur when simulations are run at their program-specific default values. Finally, we discuss what was required to automate this conversion and comparison.

**Keywords** molecular dynamics, simulation validation, molecular simulation

## Introduction

The goal of the ongoing SAMPL blind prediction challenges [1–4] is to compare purely computational blind predictions of thermodynamic properties, such as hydration free energies, partition coefficients, and binding free energies, for a range of both model and more realistic situations. Such blind prediction challenges can be very useful in identifying unexpected reasons for differences between methods that should, in theory, yield the same result. For example, even when the same program is used with what is listed as the same force field, significant differences can be obtained. In the SAMPL4 blind test, two different sets of simulations performed with GROMACS, TIP3P water, and GAFF/AM1-BCC parameterization had differences of  $0.5 \pm 0.1$  kcal/mol that were ultimately tracked down to whether the large host molecule had AM1/BCC partial charges determined fragment-wise or for the entire molecule at the same time, the level of detail that often does not make it into publication. [5]

One particular question that can be difficult to address is to what extent methods that are supposed to be identical will give different results with different simulation programs. Therefore, one of the tasks carried out in preparation for SAMPL5 was to prepare starting simulations in several of the most common molecular simulation packages (AMBER [? ], GROMACS [6], LAMMPS [7], DESMOND [? ]). To ensure that the simulations were translated correctly, it was also necessary to compare the evaluated energies of the initial configurations in the native simulation programs for each file format to ensure that the translation had been done correctly. This also involved an analysis of which different simulation conditions and parameter choices were necessary for these simulation programs to give the same, or substantially the same, energy. In order to make this task feasible, this process was necessarily highly automated. We present here the results of this comparison. One important change from the initial work carried out for SAMPL5 and this one is adding the generation of CHARMM-format starting files as well as the initial energies generated with the CHARMM simulation program.

In this study, we have chosen to compare only the energies of initial structures and not the values of thermodynamic observables such as average energy, nor more complicated physical observables such as hydration free energies which require multiple simulations. The reason for limiting this study to the evaluation of single point energies is to better deconvolute the different tasks that molecular simulation engines perform.

The first task that a molecular simulation engine has is to take an molecular configuration and a model (i. e. a specification of all force field parameters) and from these ingredients generate the energy of the model in that configuration and, in molecular dynamics approaches, also the forces acting on each particle. Next, given the assignment of energies and forces to a configuration, a molecular simulation engine then also generates a sequence of configurations that belong to a desired ensemble of that model, such as the microcanonical

(NVE), canonical (NVT), or isobaric-isothermal (NPT) ensemble, with their corresponding probability distribution for each configuration.

However, this second task requires a large number of different decisions that are made mostly independently of the assignment of energy to a set of coordinates. Slightly different integration methods will give rise to slightly different ensembles. [?] To pick one example, molecular dynamics averages are slightly dependent on the time step, and using longer time steps means the simulation is occurring at a slightly higher effective temperature, which may or may not be detected in the temperature estimator of the simulation. [?] Different thermostats will converge to the correct ensemble (if they are actually correctly implemented thermostats) but the speed at which they approach to that value can vary. Different programs have different recommended integration schemes. Addressing the multitude of possible ways that simulations could differ using different integration schemes is beyond the scope of this study.

Additionally, a difference between the output of programs with theoretically the same model occurs when the energy and forces are approximated in order to increase the number of molecular dynamics or Monte Carlo steps in a fixed amount of computing time. For example, Lennard-Jones terms may be truncated at some separation distance with some sort of approximation for longer distances [8, 9, 18], or Coulombic interactions long-range terms may be approximated by an interpolated mesh [10] rather than a direct lattice sum. Not only does each program make different default choices, most of these choices are left up to the user, meaning different results can be obtained by different users of the same code, and the recommended or default behavior of each code will almost certainly differ from program to program to some degree.

Understanding what the effect of the choice of such a wide range of approximations for even simple quantities such as enthalpy or density is extremely time-consuming, and has only been done partially systematically. Simulation observables are ensemble averages, and are thus statistical quantities with associated statistical error. Since the uncertainty scales as (simulation time)<sup>-1/2</sup>, increasing the accuracy by a factor of 10 requires 100 times as much simulation time. Small differences in the parameters used to run the simulations give rise to similarly small changes in the ensemble averages. If we attempt to calculate a small difference between ensemble averages  $\langle O \rangle_1$  and  $\langle O \rangle_2$ , carried out at simulation parameter sets 1 and 2, with statistical uncertainties  $\sigma_1$  and  $\sigma_2$ , the error in  $\langle O \rangle_1 - \langle O \rangle_2$  will be  $\sqrt{\sigma_1^2 + \sigma_2^2}$ . If  $\langle O \rangle$  is, for example, the enthalpy of a calculation, it might be of order -100,000 kJ/mol. For a given amount of simulation time, if the relative error in  $\langle O \rangle$  is 0.0001% or about 10 kJ/mol, then error in  $\langle O \rangle_1 - \langle O \rangle_2$  will be of order 14 kJ/mol. Clearly, it would be important to know if a change in a simulation parameter changed the an enthalpy difference by anywhere near 14 kJ/mol. To take that uncertainty down to, say, a 95% confidence interval of 1 kJ/mol would take approximately  $(2 \times 14)^2 \approx 800$  times as much simulation as determining  $\langle O \rangle$  itself to one part in  $10^{-6}$ . Reweighting approaches have recently been developed to include the correlation between variables, allowing in may

cases the uncertainty to be calculated by one to three orders of magnitude more efficiently. [11] However, even with this acceleration, it is still extremely expensive. For this additional reasons, enumerating all the possible ways that simulation parameters affect ensemble observables is beyond the scope of this study.

Such comparisons are even harder for simulations requiring multiple simulations, such as free energy calculations to obtain solvation free energies or binding affinities [?]. The expense of such approaches requires the development of significant new methodologies in order to obtain reasonably efficient results for parameter sensitivity tests of free energies [12]. These more complex observables are calculated using a large number of different methodologies, all of which have new parameters, with different statistical accuracies and inherent biases. The number of different approaches with different domains of applicability can significantly confound the ability to truly understand the effect of underlying assumptions.

This lack of systematic study of the effect of many of these approximations is partly due to the fact that most choices actually do not have significant effects on simulation observables. The main reason for this is that many default choices were made with good underlying physical reasoning, and thus lead to relatively comparable and reliable results. This makes it rather unrewarding to carry out such computationally intensive searches to find the few choices that do significantly affect simulation observables.

However, another reason for the lack of systematic study of molecular simulations is the fact that unless the underlying energy functions are the same between different programs, then it is very difficult to compare the results obtained for sensitivity of a given setting obtained with one program with that obtained by a separate program. It is always challenging to obtain comparable results using one simulation engine with a second simulation engine, because the input configurations and model must be converted, which either is done using painstaking manual copy-and-pasting, one-off scripts, or occasionally existing scripts that can convert from one specific program to another. Some examples include ACPYPE, a converter from AMBER to GROMACS [13], CHAMBER [14] a converter from CHARMM to AMBER, `amber2lmp`, a script converting between LAMMPS and AMBER files. There are other resources which do not convert directly, but will build the same system in multiple programs, such as CHARMM-GUI. [15]

In this study, we will therefore focus on the automated conversion of molecular simulation input files using to the extent possible automated all-to-all conversion tools, and the comparison and validation of the energies of single configurations among these programs. This validation serves as a necessary building block for later studies to more easily evaluate the differences between simulation engines in calculating simulation observables, and the comparison of more advanced simulation methods between different simulation programs.

## Methods

The molecular interconversion software programs InterMol (<https://github.com/shirtsgroup/InterMol>) and ParmEd (<http://parmed.github.io/ParmEd/>) were used to perform comparisons between five different simulation input parameter files and engines. InterMol is designed as a generalizable all-to-all converter between molecular simulation file formats; however, it currently only has full support for GROMACS, LAMMPS, and DESMOND file formats. ParmEd is [Jason: fill in more here] a molecular topology editor that also provides conversion functionality between GROMACS, AMBER, and CHARMM force field formats.

We took advantage of this overlap in conversion functionality to provide output files in five formats. The process is as follows: We took files initially parameterized in AMBER format using AmberTools and read them using ParmEd. We then used ParmEd to convert them into GROMACS input file formats. We then convert from these GROMACS files into LAMMPS and DESMOND input files using InterMol. ParmEd was also used for this study (though not the original SAMPL5 release) to convert the AMBER simulation files into CHARMM simulation files directly.

We use the InterMol `convert.py` tool to manage all of the conversions (including interfacing with the ParmEd API). InterMol allows control of simulation input parameters by either reading a user-defined (or default) sample simulation parameter file (for DESMOND, AMBER, and GROMACS) or inserting user-defined strings defining nonbonded terms into the parameter and topology files (LAMMPS and CHARMM). Full any-to-any conversion is not yet possible using the combination of tools so far, since ParmEd cannot yet convert between some dihedral formats, making it impossible to write many valid GROMACS files into CHARMM or AMBER formats.

We use the 22 host-guest molecules distributed as part of the SAMPL5 blind challenge, with 10 ligands bound to the CBClip, 6 ligands with the octa-acid OAH host, and 6 ligands with the octa-acid OAMe host. [?] An idealized model of the 3D structure of host CBClip was provided by Prof. Lyle Isaacs. The starting 3D structures of hosts OAH and OAMe were built manually with MOE and partly energy minimized. The initial structures of free guest molecules were found via the conformational search feature in MOE. For CBClip, the experimental studies were done at pH 7.4, so the hosts four sulfonic acid acids were treated as fully ionized, for a net host charge of -4. For the octa-acids, OAH and OAMe, the experimental studies were done at pH 11.5, so all eight carboxylic acids were treated as fully ionized, for a net charge of -8. The protonation states of all guest molecules were also assigned based on their expected pKas and the experimental pH values, as shown in the figures above, and were assumed to remain the same on binding their respective hosts.

Partial charges were generated with the restrained electrostatic potential (RESP) fitting procedure, with electrostatic potentials at the HF/6-31G\* level, as implemented in Antechamber. Bonded and van der Waals parameters were assigned by GAFF [16] in Antechamber. For the octa-acids, which have a

well-defined hydrophobic cavity, the bound conformations were set up with the guests' ionized groups at the opening and their hydrophobic parts in the cavity. For the CBClip host, the positions of the guests in the binding site were constructed by manual docking in MOE. Each bound complex was placed in a cubic simulation box with edge length of about 4 nm, and containing 2100 TIP3P (non-modified) water molecules. Sodium ions were added to neutralize all systems. Given the low concentration of the buffer used in experiments, no extra ions were added to mimic the buffer. The sodium ions were modeled with the TIP3P-specific sodium parameters of [17]. Each system was then subjected to a short equilibration phase (first NVT, then NPT) to heat the system and change the volume so the pressure would be about 1 atm. [MRS: how short? What was done precisely?] The solutes were restrained during the entire process, so only the environment was relaxed. Note that the AMBER .rst7 files contain velocities consistent with a temperature of 298.15 K.

For this study, the most up-to-date releases of all molecular dynamics simulation programs were used. In most cases, this resulted in very little difference in the results between the current study and the SAMPL5 study, but in some cases as noted, the results do change. Units are given in SI units (kJ/mol and nm, for example), though different programs use different default units. [QUESTION TO ALL: what do people think about units? I'd rather not be switching back and forth from kJ/kcal and nm/Å. And if I pick one set of units, SI would be the 'right' one]

The five programs were:

- **AMBER**: Energies were calculated originally for SAMPL5, with `sander` as included AmberTools 14, but for the current study `sander` from the most recent AmberTools 16 were used.
- **GROMACS**: Energies were calculated originally and here with GROMACS 5.0.4, compiled in double precision.
- **DESMOND**: Energies were calculated in the original SAMPL5 release with 3.6012 (distributed as part of the Schrödinger 2013 package for academic use) but all tests are performed here with version X version 4.5 (distributed as part of the Schrödinger 2016-1 package for academic use). Rather than directly writing the DESMOND .dms files, the automated conversion routines were written to create MAESTRO .cms files.
- **LAMMPS**: Energies were calculated with the April 5, 2014 build in the SAMPL5 release, and the Feb 16, 2016 release in the current study. Only the additional modules to run atomistic simulations were installed.
- **CHARMM**: Energies were only generated for this study, with developmental version 40b2 of the charmm-lite free package.

All programs were compiled in RHEL 7 with the gcc 4.8.5 compiler suite.

It is difficult to choose simulation parameters that agree among all simulation engines: for example, each program generally has different types of default switching functions to taper nonbonded interactions. For this comparison, we therefore chose for our nonbonded methods that were sufficiently

Table 1: Using an analytical correction, the van der Waals energy due to the Lennard-Jones interactions are essentially independent of cutoff, with a total change of 0.001% in the total van der Waals energy for the analytic long range correction in GROMACS (and similar to other programs) and and 0.00008% with the isotropic periodic sum in CHARMM, over a change of 0.3 nm cutoffs.

Distance (nm)	GROMACS Potential Energy (kcal/mol)	CHARMM Potential Energy (kcal/mol)
1.5	2921.4840	2921.54699
1.4	2921.4923	2921.54623
1.3	2921.5265	2921.54597
1.2	2921.5246	2921.54456

cutoff independent that differences in the cutoff scheme between programs would minimally affect the results.

For electrostatic interactions, we chose either particle mesh Ewald (PME) implementations (CHARMM, AMBER, GROMACS, CHARMM) or particle-particle particle-mesh (PPPM) methods (LAMMPS). We chose a cutoff of 1.5 nm for both Coulomb and van der Waals interactions to eliminate much of the issues with errors at short range cutoffs. We chose a real space error cutoff of  $1 \times 10^{-8}$ , which corresponds to a  $\kappa$  (or  $\beta$ ) parameter of 0.020822755 nm. For PPPM, we chose a tolerance of  $1 \times 10^{-8}$ , which was necessary to reduce the error below [MRS: look up the numbers on this.] For AMBER and CHARMM, we used a PME mesh grid of  $48 \times 48 \times 48$  grid points with 4th order interpolation. DESMOND allows significantly less control over the PME parameters at the MAESTRO interface level, and we used a PME relative tolerance of  $1 \times 10^{-10}$  [MRS: look up what that setting means again]

For Lennard-Jones interactions, we avoid the problems of trying to match switching schemes between programs, which are usually quite different, by using an abrupt cutoff to zero potential. This approach is not recommended for running molecular dynamics simulations, as it creates a mismatch between forces and energies, but which is reasonable for comparing simulation energies. An analytic isotropic long-range correction was used for LAMMPS, AMBER, DESMOND, and GROMACS [8, 18], with the isotropic periodic sum approach [9] used for CHARMM. At this longer range, the results become essentially independent of the precise cutoff for both methods, though the isotropic periodic sum is less cutoff dependent, as seen in Table 1. This cutoff independence is expected for systems that are homogeneous at long range, such as a host-guest system surrounded by water, but will not be cutoff independent for a heterogeneous system such as a lipid bilayer or a liquid/vapor interface [19].

We also ran the test with an attempt to be as close to default parameters as possible. For AMBER, we use a 0.9 nm cutoff, with the same Ewald parameters ( $48 \times 48 \times 48$  Fourier points in the grid), with the isotropic analytical dispersion correction included for Lennard-Jones [MRS: is this an abrupt cutoff, or is it scaled somehow?] For GROMACS, a Fourier spacing of 0.1 nm is used For



	AMBER		GROMACS		LAMMPS		DESMOND		CHARMM	
	default settings	ideal settings	default settings	ideal settings	default settings	ideal settings	default settings	ideal settings	default settings	ideal settings
van der Waals cut-off	1.5 nm, abrupt	0.9 nm, abrupt	1.5 nm, abrupt	0.9 nm, abrupt	1.5 nm, abrupt	0.9 nm, abrupt	1.5 nm, abrupt	0.9 nm, abrupt	1.5 nm, abrupt	0.9 nm, abrupt
Coulombic cut-off	1.5 nm real space	0.9 nm real space	1.5 nm real space	0.9 nm real space	1.5 nm real space	0.9 nm real space	1.5 nm real space	0.9 nm real space	1.5 nm real space	0.9 nm real space
Long-range electrostatics	Ewald, Fourier points 48 × 48 × 48, order 4, real space error 10 <sup>-5</sup>	Ewald, Fourier points 48 × 48 × 48, real space error 10 <sup>-5</sup>	Ewald, Fourier points 48 × 48 × 48, real space error 10 <sup>-5</sup>	Ewald, Fourier points 48 × 48 × 48, real space error 10 <sup>-5</sup>	PPPM, 10 <sup>-8</sup> tolerance	PPPM, 10 <sup>-8</sup> tolerance	Ewald, 10 <sup>-10</sup> tolerance	Ewald, 10 <sup>-10</sup> tolerance	Ewald, Fourier points 48 × 48 × 48, 10 <sup>-8</sup> tolerance	Ewald, Fourier points 48 × 48 × 48, 10 <sup>-8</sup> tolerance
Long-range van der Waals	Isotropic correction	Isotropic correction	Isotropic correction	Isotropic correction	Isotropic correction	Isotropic correction	Isotropic correction	Isotropic correction	Isotropic correction	Isotropic correction

Table 2: Key nonbonded term setting for both default and ideal energy validation tests[NOTE: I’m not sure this table is the best way to summarize things. Formatting is not ideal, obviously.

LAMMPS, we use pair\_style lj/cut/coul/long 9.0 9.0. We include a dispersion correction, and use PPPM, with 10<sup>-8</sup> [MRS: right choice?].

We also examined how dependent the energy differences are on the individual configurations. For twelve of the systems (the six OAMe and the six OAH octa-acid host-guest systems), we take 20 different configurations. These configurations were generated with electrostatic parameters and Lennard-Jones parameters as listed in the ‘default’ parameter section. Temperature was maintained at 298.15 K with the Langevin thermostat with a damping constant  $\gamma$  of 1 ps<sup>-1</sup> with a timestep of 2 fs with constrained bonds [JANE: is this correct on the constraints, or were just H-bonds constrained?]. Simulations were started from the SAMPL5 example files and run for 2 ns, and configurations were taken every 100 ps.

Matching the precision of the coordinates in the files used in conversion is important to matching the energies. While keeping the precision of the input files the same, we truncated the precision of the output files by a varying number of digits of precision in order to examine how the energy components are affected. Note that lower precision files will not have an affect on ensemble averages if such files are only used as starting points for simulation. But it will matter quite a bit if output configurations are used for reanalyzing energy contributions.

Another source of differences in energy relates to the precision of the binary. We therefore also look at the same version of GROMACS compiled in double precision (the precision that is used in the reference calculations) and in single precision.

## Results

We first compare the 10 different energy terms between five different simulation programs with the ideal nonbonded parameters, with results shown in Table 1. All results are averaged over the 22 host-guest molecules included in the SAMPL5 blind prediction challenge. To avoid picking a favored reference program, we look at the deviation of each term from the average of all five programs, calling this the “program average” for the molecule. “Potential energy” is the total potential energy of the system, but is not the total over all 9 other energy terms, since several of these terms are sums of other terms: “Bonded” is the sum of “Bonds”, “Angles”, “All dihedrals” (including both improper and proper dihedrals), “Electrostatic” is the sum of “Coulomb 14”, Coulomb short range and Coulomb long range forces, “van der Waals” is the sum of “LJ-14” and van der Waals short and long range terms, and “Nonbonded” is the sum of “Electrostatic” and “van der Waals” terms.

We examine three statistics: the average differences from the program average over all molecules, the average of the absolute value of the difference, and the average of the relative absolute value of the difference. Each statistic gives some additional information about the system. The average gives information about the manner in which energy component deviates from the program average, while the absolute value of the differences shows the magnitude of the deviation, avoiding any cancellation due to different signs. Because many terms are much smaller than others, for example, the bonded energy terms being two to three orders of magnitude smaller than the electrostatic term, the relative absolute difference shows the fractional error in each term.

We find that the bonded terms match very well between all programs. Average differences from the program average are below 0.05 kJ/mol in magnitude for all terms for all programs, and usually about an order of magnitude lower (CHARMM was slightly higher than the others), and around or below 0.002 kJ/mol for the bonded term for all programs. Average absolute differences in the total bonded term are below 0.004 kJ/mol for all programs except CHARMM. CHARMM’s average absolute value is 0.007 kJ/mol, but is dominated by differences in the dihedral terms; bond and angle terms are as low as other programs.

The average relative absolute quantities are perhaps a more important comparison metric, since it is an intensive quantity; the total deviation of the energy will of course become larger as the system becomes larger. Here, we see that the bonded terms are accurate to generally about 3 parts in  $10^{-6}$ , with CHARMM slightly higher at 7 parts in  $10^{-6}$ . Given that this is approximately the limit one would see in single precision calculations, and given the fact that some programs only output energies to four (AMBER) or five (CHARMM) decimal places, or eight significant digits total (LAMMPS) this seems for all programs to be a reasonable amount of agreement for most purposes, demonstrating that the conversion process has successfully copied parameters with the correct functional form for bonded interactions between all of the programs

of interest, and the energies are being calculated in a consistent way for these bonded interactions.

[MRS: need to verify gromacs single precision numbers again]

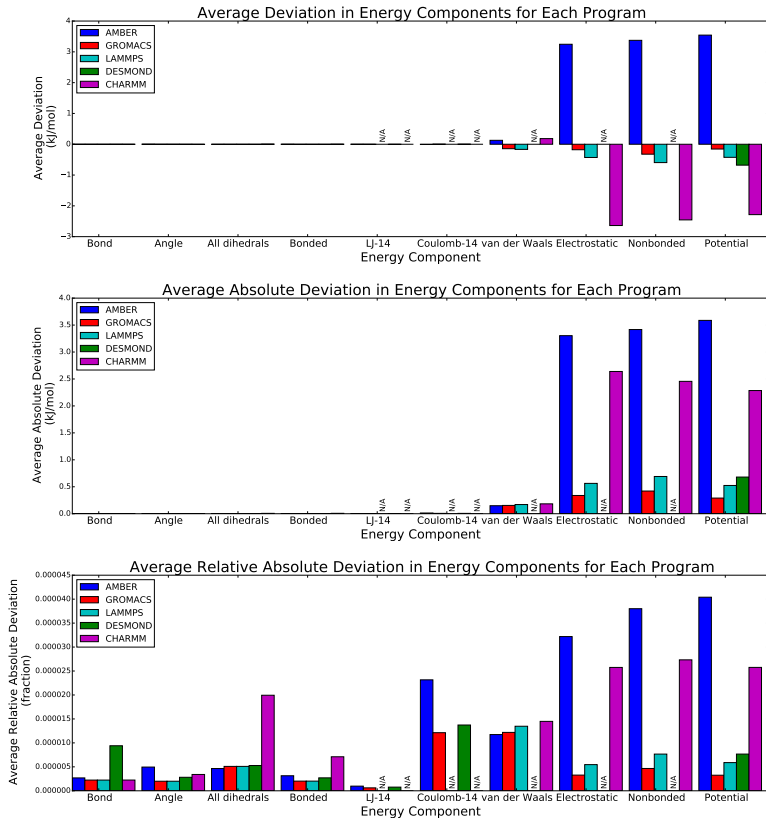


Fig. 1: We compare the variation of 10 different energy terms between five different simulation programs (AMBER, GROMACS, LAMMPS, DESMOND, and CHARMM) for the 'optimal' choice of cutoff parameters. For each term, we plot the deviation of each program from the average of all programs (the program average), to avoid choosing a single arbitrary reference program. All statistics are averaged over 22 host-guest molecules. We plot the average deviation (top), the absolute average deviation (middle), and relative absolute average deviation (top).

We next examine the nonbonded interactions. Coulomb 1-4 and van der Waals 1-4 interactions are a good measure of whether the nonbonded parameters are being copied correctly, as they generally are all calculated with real space interactions and are shorter range than any reasonable cutoff, and thus their comparison is not affected by nonbonded parameter choice.

We see that, like the bonded interactions, the 1-4 interactions, when available, are in good agreement. In all available cases, the van der Waals 1-4

Table 3: RMSD in kJ/mol of different energy components in GROMACS 5.0.4 from AMBER energies as GROMACS Coulomb constant is varied, calculated over all 22 host-guest systems.

	Coulomb-14	Electrostatic	Total Potential
GROMACS original constant	0.00522	0.789	0.872
AnteChamber constant	0.000064	0.241	0.225
Percent difference explained	98.8%	69.5%	74.2%

interactions have relative absolute differences at least a factor of 2 better than even the bond and angle interactions, at about 1 part in  $10^{-7}$  LAMMPS and CHARMM do not calculate 1-4 interactions independently, but some post-processing tricks involving subtracting energies with different input parameters show that the CHARMM van der Waals 1-4 energies have similar accuracy, in particular being generally within  $10^{-5}$  of AMBER.

The story from the Coulombic 1-4 interactions is more complicated. Looking at the absolute difference, we see that the difference of GROMACS and DESMOND from the program average is about half of what the difference is from AMBER. In this case, the difference in Coulombic 1-4 interactions between GROMACS and DESMOND is less than 10% of what the differences is between AMBER and the other two programs is. Since the LJ 1-4 parameters are in good agreement, the difference must come from some other source.

After some analysis of the data, it becomes clear that the value of Coulomb’s constant, the constant of proportionality in  $U = k \frac{q_1 q_2}{r}$  that is the cause of the differences in the Coulomb 1-4 terms. In Table 5, we show the value of the Coulomb constant in a range of different simulation programs compared to the NIST 2014 CODATA value. We list “AnteChamber” instead of `sander` as in AMBER, the constant is set by multiplying the charge by  $\sqrt{k}$  in the input file, rather than set internally by the molecular dynamics engine. We use as a control of this test a comparison by looking at the RMS difference in energy between AMBER energies and GROMACS energies evaluated with it’s 5.0.4 Coulomb constant, and then with GROMACS recompiled with the AMBER Coulomb constant. Results are shown in Table 3. We see that matching Coulomb’s constant removes 98.8% of the difference in the Coulomb 1-4 term between the two programs, 69.5% of the total electrostatic energy difference, and 74.2% of the total potential energy difference between the two programs.

Nonbonded interactions are harder to get in good agreement between programs. Validating the van der Waals and Coulombic 1-4 interactions demonstrates that the the Lennard-Jones parameters and Coulombic charges are correctly created in the other file formats. In that sense, validating the conversion of file formats can be done without comparing the long-range interactions. However, if we are interested in comparing results of programs, we will need to compare the entire potential energy, including these terms.

One complication is that different programs both calculate and print out the different components of nonbonded interactions differently, such as the direct space energy, the Fourier space energy, the Ewald self term, and so forth.

Thus, it is sometimes difficult to look at anything except the total Lennard-Jones or total electrostatic energy, making it harder to determine exactly the source of any discrepancy between programs, and motivating our attempt to find 'ideal' parameters.

Errors in the nonbonded energy terms are always much larger in magnitude for any liquid phase simulation, since there are many more intermolecular interactions than intramolecular interactions. It is therefore instructive to look first at the average relative absolute deviations from the program average. For GROMACS, AMBER, LAMMPS, and CHARMM, the fractional difference in the van der Waals energy is approximately  $1 \times 10^{-5}$ , which is 2-5 times larger than the difference in the bonded energy (DESMOND does not separate this energy out). GROMACS and LAMMPS are generally closer to each other, usually within one part in  $10^6$ , and CHARMM and AMBER are clustered together, though not as closely as GROMACS and LAMMPS. Deviations are likely due to differences in the calculation of long range interactions.

Differences from the program average in the total electrostatic energy are smaller than errors in the total van der Waals energy for GROMACS and LAMMPS, but are significantly larger for AMBER. As seen above, a large portion of the electrostatic deviation of AMBER from those two programs is because of the inconsistent choice of Coulomb's constant. Although CHARMM also has a relatively inaccurate Coulomb's constant, the differences in the CHARMM potential energy are in the other direction from AMBER, indicating a difference in the way the electrostatic energy is calculated from the other programs. For AMBER, about 70% of this deviation is due to the Coulomb choice, leaving significantly less of the deviation from other programs due to other choices in nonbonded parameters. An adjustment in CHARMM's Coulomb's constant would actually make the energy further from the other three programs. However, it is important to notice that this fraction difference is still on the order of  $2.5 \times 10^{-5}$ , likely too small to matter for most quantities of interest.

The deviations in the program average of the total potential energy is dominated by the differences in the nonbonded terms, since those are so much larger than differences in the bonded energy. For CHARMM and AMBER, differences in the electrostatic nonbonded energy dominates. DESMOND total potential energies differences from the program average are almost the same as GROMACS and LAMMPS, indicating that since the bonded interactions match the two programs well, the nonbonded also must match relatively well.

We also are interested in the deviations of energies as a function of the number of coordinates used in the output file. The results of the comparison between AMBER (full precision input) and GROMACS (reduced precision output) are shown in Fig. 3. We choose only to show GROMACS as the other programs show similar behavior. We plot the  $-\log_{10}$  of the average relative absolute difference between the GROMACS energy and the AMBER energy as a function of the number of decimal places in the output GROMACS coordinates from 8 digits after the decimal place (measured in nanometers) down to 4 after the decimal place, what one would obtain from a file downloaded

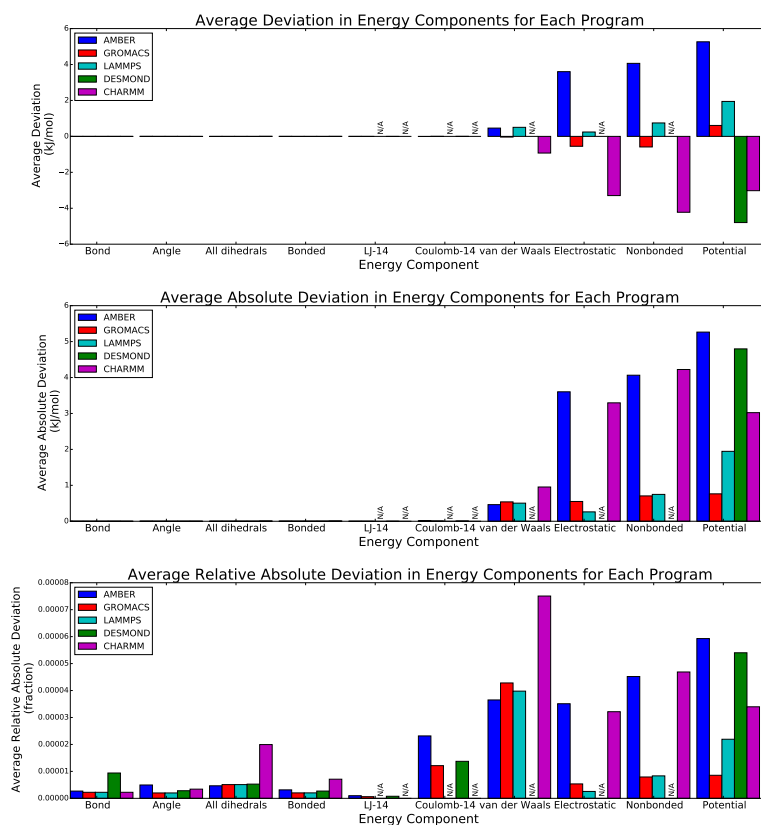


Fig. 2: We compare the variation of 10 different energy terms between five different simulation programs (AMBER, GROMACS, LAMMPS, DESMOND, and CHARMM) for the 'default' choice of cutoff parameters (described in table). As above, for each term, we plot the deviation of each program from the average of all programs, to avoid choosing a single arbitrary reference program. All statistics are averaged over 22 molecules. We plot the average deviation (top), the absolute average deviation (middle), and relative absolute average deviation (bottom). Nonbonded potential parameter deviations are approximately a factor of 2 larger than using the 'ideal' parameters.

from the PDB. We see that the total energy loses approximately 0.75-1 digits of relative precision in the energy for each digit of precision of coordinate lost. Since the van der Waals and electrostatic nonbonded energies contribute the majority of the potential energy, their loss of precision mirrors the overall loss of precision. Interestingly, the bonded and 1-4 terms are less sensitive, not losing much precision until getting down to 5 or fewer digits after the decimal point. However, losing just a few digits of precision completely washes out any other source of error, demonstrating the importance of matching the coordinates to high precision in order to validate the rest of the conversion.

We are also interested in how much changing the precision of the binaries. We focus on the comparison between single and double precision GROMACS,

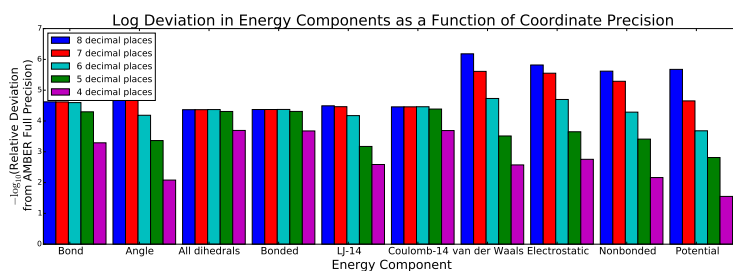


Fig. 3: Matches in energy between converted files become rapidly worse as the number of digits of precision in the converted files decreases. We plot  $-\log_{10}$  of the average relative absolute value in each energy term between AMBER and GROMACS, with fixed input coordinate precision, and variable output precision with the number of decimal places in the coordinates in nanometers, varying from 8 down to 4, the precision of a standard PDB file.

as it is specifically designed to be compiled in either single and double precision, though the single precision is the default version most simulations are run with. In Table 4, we compare the RMS differences averaged over all 22 compounds between the two GROMACS binaries, AMBER and single precision GROMACS, and AMBER and double precision GROMACS. This comparison allows us to see both the magnitude of the difference due to changes in binary precision, and how much this difference affects the comparison to, for example, AMBER.

We see that the differences between single and double precision for bonded terms is 2-8 times larger than the difference between AMBER and double precision GROMACS, usually dominating the difference between AMBER and single precision GROMACS. Differences between the precisions for LJ-14 is about equal to differences between either precision and AMBER. Differences between precisions for Coulomb-14 is as low as the difference between Coulomb-14, which is of course much less than the GROMACS to AMBER difference, because of the previously described difference in Coulomb constant. The differences in precision for the total van der Waals is an order of magnitude less than the difference between AMBER and either GROMACS precision caused by differences in calculating the nonbonded terms. However, single to double precision caused significant difference in the overall electrostatic term, as large as the magnitude between GROMACS and AMBER. Because the total van der Waals energy changes relatively little between precisions, it is likely that the short-range electrostatics (which are functions only of the distance) are also relatively accurate, and it is the Ewald summation part that results in the change of accuracy.

We are also interested in how much of the differences between programs vary with the configurations of each molecule. For example, if we were to take different configurations of the same molecule, would we get similar deviations from the program average? We ask this question by taking the 12 octa-acid hosts, and generating 20 configurations as described in the Methods section using NVT molecular dynamics. The average over these 20 configurations is

E term	$\text{RMS}(E_{\text{single}} - E_{\text{double}})$	$\text{RMS}(E_{\text{amber}} - E_{\text{single}})$	$\text{RMS}(E_{\text{amber}} - E_{\text{double}})$
Bond	0.000066	0.000068	0.000008
Angle	0.000044	0.000043	0.000007
All dihedrals	0.000015	0.000031	0.000018
Bonded	0.000081	0.000086	0.000011
LJ-14	0.000013	0.000020	0.000025
Coulomb-14	0.000007	0.001250	0.001251
van der Waals	0.001894	0.021756	0.023116
Electrostatic	0.218874	0.403839	0.189265
Nonbonded	0.217209	0.422827	0.209207
Potential	0.217134	0.422781	0.209214

Table 4: Differences between double and single GROMACS energy evaluations are of similar magnitude to the differences between AMBER and GROMACS, but are dominated by differences in the long-range electrostatics. All energies in kJ/mol.

therefore an rough approximation to the ensemble average energy of the system.

We then compare the RMSD from the program average  $\sigma_{\text{config}}$ , averaged over all  $12 \times 20 = 240$  configurations, and the RMSD of the average energy of all configurations of the same molecule, then averaged over the 12 host-guest systems  $\sigma_{\text{molecule}}$ . If the variation from program to program is independent of configuration, and only dependent on the differences between molecules, then we would expect that the two RMSDs would be roughly equal (low conformation dependent variation). If instead the variation is mainly dependent on configuration, then the RMSD from the configurationally averaged deviations from program averages ( $\sigma_{\text{molecule}}$  would be significantly smaller (approximately  $\sqrt{1/20} \approx 22\%$  of the value). Note that the RMSD of the conformationally averaged values must necessarily be lower than the RMSD over all configurations and molecules. The extent to which it is smaller shows how much of the variation is inherent to the molecules, and how much is only dependent on the configurations.

We can quantify this difference in the source of variation by calculating the fraction of the total variation due to conformational variability, calculated as  $\frac{\sigma_{\text{config}}^2 - \sigma_{\text{molecule}}^2}{\sigma_{\text{molecule}}^2}$ , for each energy component. If this quantity is low, then variation is mostly due to differences between molecules, not configurations. If it is near one, then variation between programs is mostly due to changes in conformation.

We can observe the results in Figure 4. At one extreme are the bond energies, which have only about 8% of the total variation between programs due to configurational variation, near the minimum of  $1/20 \approx 5\%$ . Most of the differences are due to differences between the molecules. Similarly, the variations in van der Waals 1-4 interactions are mostly due to differences between molecules

At the other extreme are the Coulomb 1-4 terms, where almost 100% of the variation is due to conformational variation: after averaging the differences over molecules, there is very little variation left. Similarly, almost 100% of the variability in the total van der Waals energy is due to conformational



variability. Variation in angle energies from the program average again likely relatively dependent on configuration (around 80%).

Total electrostatic variation is one of the few energy components where the fraction of variation depends significantly on the programs. For AMBER, it is not very dependent on configuration; for other programs, it is much more dependent on configuration. This is likely because of differences in the Coulomb constant and in the treatment of long-range electrostatic energies, as the long-range forces are much less-dependent on individual molecular distances, instead being dependent on the average distribution of charge within the system, which does not change significantly for a host-guest system over time, and which will scale with the changes in the Coulomb constant. On the other hand, the Coulomb 1-4 interactions are dominated by the variability of which atoms are closest to each other at any given time.

The analysis in the variation of the total potential energy conclusion illustrates again that the dominant reason that the molecular simulations differ are the evaluation of long-range interactions, especially the electrostatics, and the choice of the Coulomb constant. We find that the total variation of the potential energy, like total potential energy itself, depends almost entirely on the nonbonded terms. Since the van der Waals variation between programs is almost entirely conformation dependent, with very little deviation in programs between the ensemble average estimate for each molecule, the conformational dependence of the total energy is essentially determined by the conformational dependence of the electrostatic energy; the bonded terms are essentially irrelevant.

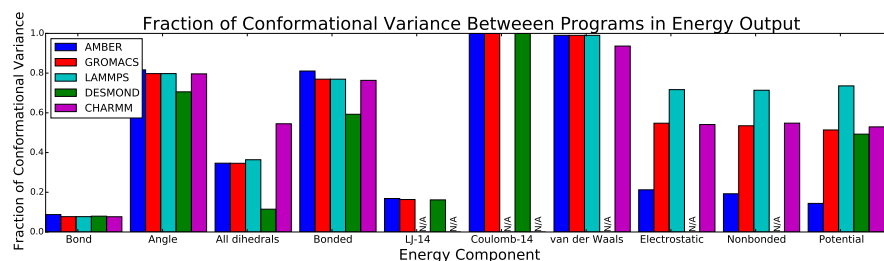


Fig. 4: Fraction of variation from the program average due to conformational variability instead of molecular variability.

## Discussion

### Issues in file conversion

Creating true all-to-all functionality is particularly difficult. There are a number of one-to-one conversion utilities: for example, ACPYPE [13]

Table 5: Values of Coulomb’s law constant currently used in molecular simulation programs compared to the value of 332.06371302(32) calculated from NIST CODATA 2014. Specific versions of the programs used are described in the text. Two versions of GROMACS are listed because SAMPL5 energies were originally generated with version 5.0.4, but the value has been changed since then. Coulomb’s constant  $f$  in units of  $\text{kcal}\cdot\text{mol}^{-1}\text{\AA}e^{-2}$  was calculated as  $k_e N_A e^2$ , where  $k_e$  is Coulomb’s constant defined exactly in  $\text{N m}^2\text{C}^{-2}$ ,  $N_A$  is Avogadro’s number, and  $e$  is the elementary charge from NIST CODATA 2014. [MRS: I’m using non-SI units because that’s what actually hard coded in the programs, but can easily switch to be entirely in SI]. Uncertainties in  $f$  were calculated using standard error propagation using NIST CODATA 2014 values at the correlation coefficient between  $N_A$  and  $e$  of -0.9985, also from NIST CODATA 2014. At less than 1000 standard deviations, however, errors due to the Coulomb constant are no longer the largest source of error.

Program	Value	$\sigma$ from NIST 2014 reference value
Antechamber	332.0522173	51000
GROMACS ( $\leq 5.0$ )	332.063693	89
GROMACS ( $> 5.1$ )	332.0637138	3.3
CHARMM	332.054	43000
LAMMPS	332.06371	13
DESMOND	332.063762	220
NAMD	332.0636	510

Both InterMol and ParmEd automatically convert units between simulation input files, removing the needs for manual unit conversion.

#### Issues in matching energies

It is difficult to assign a label “proper” or “improper” to a given dihedral, since in different programs the same functional form is used for both types. We thus put all of the energy together as dihedral energy.

The results strongly suggest that all molecular simulation programs should choose a sufficiently consistent value for Coulomb’s constant. A value off by 0.01 is simply not accurate enough. The results here suggest that one the deviation is below 0.0001, any additional error contributes less than other sources of error, so a value of  $332.06371 \pm 0.00005$  should reduce this sort of discrepancy below the level of differences created by other programs. This level of agreement is present in all current programs with the exception of CHARMM and AMBER, with GROMACS, at the edge of that range, recently improving the precision by a factor of 4 in the 5.1 release.

LAMMPS supports a large number of different functional forms that are not supported in other systems, as it has generally been used for a wider range of materials than the other programs.

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## References

1. Muddana HS, Fenley AT, Mobley DL, Gilson MK (2014) The sampl4 host-guest blind prediction challenge: an overview. *J Comput Aided Mol Des* 28:305–317
2. Muddana HS, Varnado CD, Bielawski CW, Urbach AR, Isaacs L, Geballe MT, Gilson MK (2012) Blind prediction of host-guest binding affinities: a new SAMPL3 challenge. *J Comput Aided Mol Des* 26(5):475–87
3. Geballe MT, Skillman AG, Nicholls A, Guthrie JP, Taylor PJ (2010) The SAMPL2 blind prediction challenge: introduction and overview. *J Comput Aided Mol Des* 24(4):259–279, DOI 10.1007/s10822-010-9350-8, URL <http://link.springer.com/article/10.1007/s10822-010-9350-8>
4. Guthrie JP (2009) A Blind Challenge for Computational Solvation Free Energies: Introduction and Overview. *J Phys Chem B* 113(14):4501–4507, DOI 10.1021/jp806724u, URL <http://dx.doi.org/10.1021/jp806724u>
5. Monroe JI, Shirts MR (2014) Converging free energies of binding in cucurbit[7]uril and octa-acid hostguest systems from sampl4 using expanded ensemble simulations. *J Comput Aided Mol Des* 28:401–415
6. Hess B, Kutzner C, Spoel Dvd, Lindahl E (2008) GROMACS 4: Algorithms for highly efficient, load-balanced, and scalable molecular simulation. *J Chem Theo Comput* 4:435–447
7. Plimpton S (1995) Fast Parallel Algorithms for Short-Range Molecular Dynamics. *Journal of Computational Physics* 117(1):1–19, DOI 10.1006/jcph.1995.1039, URL <http://www.sciencedirect.com/science/article/B6WHY-45N1B-3N/2/58aa2a309d2ebbbe60e0f417d398b0ef>
8. Shirts MR, Mobley DL, Chodera JD, Pande VS (2007) Accurate and Efficient Corrections for Missing Dispersion Interactions in Molecular Simulations. *J Phys Chem B* 111(45):13,052–13,063, DOI 10.1021/jp0735987, URL <http://dx.doi.org/10.1021/jp0735987>
9. Wu X, Brooks BR (2005) Isotropic periodic sum: a method for the calculation of long-range interactions. *J Chem Phys* 122(4):44,107, DOI 10.1063/1.1836733
10. Essmann U, Perera L, Berkowitz ML, Darden T, Lee H, Pedersen LG (1995) A smooth particle mesh Ewald method. *The Journal of Chemical Physics* 103(19):8577–8593, DOI 10.1063/1.470117, URL <http://scitation.aip.org/content/aip/journal/jcp/103/19/10.1063/1.470117>
11. Paliwal H, Shirts MR (2013) Using multistate reweighting to rapidly and efficiently explore molecular simulation parameters space for nonbonded interactions. *J Chem Theory Comput* 9(7):4700–4717
12. Naden LN, Shirts MR (2016) Rapid Computation of Thermodynamic Properties over Multidimensional Nonbonded Parameter Spaces Using Adaptive Multistate Reweighting. *J Chem Theory Comput* 12(4):1806–1823, DOI 10.1021/acs.jctc.5b00869, URL <http://dx.doi.org/10.1021/acs.jctc.5b00869>

13. Sousa da Silva AW, Vranken WF (2012) ACPYPE - AnteChamber PYthon Parser interface. *BMC Research Notes* 5:367, DOI 10.1186/1756-0500-5-367, URL <http://dx.doi.org/10.1186/1756-0500-5-367>
14. Crowley MF, Williamson MJ, Walker RC (2009) CHAMBER: Comprehensive support for CHARMM force fields within the AMBER software. *Int J Quantum Chem* 109(15):3767–3772, DOI 10.1002/qua.22372, URL <http://onlinelibrary.wiley.com/doi/10.1002/qua.22372/abstract>
15. Lee J, Cheng X, Swails JM, Yeom MS, Eastman PK, Lemkul JA, Wei S, Buckner J, Jeong JC, Qi Y, Jo S, Pande VS, Case DA, Brooks CL, MacKerell AD, Klauda JB, Im W (2016) CHARMM-GUI Input Generator for NAMD, GROMACS, AMBER, OpenMM, and CHARMM/OpenMM Simulations Using the CHARMM36 Additive Force Field. *J Chem Theory Comput* 12(1):405–413, DOI 10.1021/acs.jctc.5b00935, URL <http://dx.doi.org/10.1021/acs.jctc.5b00935>
16. Wang JM, Wolf RM, Caldwell JW, Kollman PA, Case DA (2004) Development and testing of a general Amber force field. *Journal Of Computational Chemistry* 25(9):1157 – 74
17. Joung IS, Thomas E Cheatham I (2008) Determination of alkali and halide monovalent ion parameters for use in explicitly solvated biomolecular simulations. *J Phys Chem B* 112:9020–9041
18. Allen MP, Tildesley DJ (1989) *Computer Simulation of Liquids*. Clarendon Press, New York, NY, USA
19. Veld P Ji, Ismail AE, Grest GS (2007) Application of Ewald summations to long-range dispersion forces. *The Journal of Chemical Physics* 127(14):144,711, DOI 10.1063/1.2770730, URL <http://scitation.aip.org/content/aip/journal/jcp/127/14/10.1063/1.2770730>