

HHS Public Access

Author manuscript *J Comput Chem*. Author manuscript; available in PMC 2017 April 05.

Published in final edited form as: *J Comput Chem*. 2016 April 5; 37(9): 836–847. doi:10.1002/jcc.24274.

Evaluating Thermodynamic Integration Performance of the New Amber Molecular Dynamics Package and Assess Potential Halogen Bonds of Enoyl-ACP Reductase (FabI) Benzimidazole Inhibitors

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Abstract

Thermodynamic integration (TI) can provide accurate binding free energy insights in a lead optimization program, but its high computational expense has limited its usage. In the effort of developing an efficient and accurate TI protocol for FabI inhibitors lead optimization program, we carefully compared TI with different Amber molecular dynamics (MD) engines (*sander* and *pmemd*), MD simulation lengths, the number of intermediate states and transformation steps, and the Lennard-Jones and Coulomb Softcore potentials parameters in the one-step TI, using eleven benzimidazole inhibitors in complex with *Francisella tularensis* enoyl acyl reductase (FtFabI). To our knowledge, this is the first study to extensively test the new AMBER MD engine, *pmemd*, on TI and compare the parameters of the Softcore potentials in the one-step TI in a protein-ligand binding system. The best performing model, the one-step *pmemd* TI, using 6 intermediate states and 1 ns MD simulations, provides better agreement with experimental results (RMSD = 0.52) kcal/mol) than the best performing implicit solvent method, QM/MM-GBSA from our previous study ($RMSD = 3.00$ kcal/mol), while maintaining similar efficiency. Briefly, we show the optimized TI protocol to be highly accurate and affordable for the FtFabI system. This approach can be implemented in a larger scale benzimidazole scaffold lead optimization against FtFabI. Lastly, the TI results here also provide structure-activity relationship insights, and suggest the para-halogen in benzimidazole compounds might form a weak halogen bond with FabI, which is a well-known halogen bond favoring enzyme.

Keywords

thermodynamic integration (TI); enoyl acyl reductase (FabI); explicit solvent models; free energy calculation; implicit solvent models; halogen bond; benzimidazole-based inhibitors

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Additional Supporting Information may be found in the online version of this article.

Introduction

F. tularensis is the bacterial pathogen that causes tularemia and is a potential bioweapon. Current tularemia treatments are limited due to their toxicity or the requirement for intravenous administration.¹ Therefore, a safe and orally available small molecule is desirable in the event of a potential tularemia outbreak. Among various antibacterial targets, enoyl acyl reductase (FabI) has been proven essential in *F. tularensis*, and differs structurally from the human fatty acid synthesis complex. Hence, FabI is a promising antibacterial *F. tularensis* target, and FabI inhibitors can potentially avoid human toxicity.

Free energy calculations potentially offer a valuable ligand binding free energy estimate and could prioritize compounds for synthesis and experimental testing. There are two major categories of free energy calculations. The first category includes implicit solvent methods such as Molecular Mechanics - Poisson-Boltzmann Surface Area (MM-PBSA), Molecular Mechanics - Generalized Born Surface Area (MM-GBSA), and Linear Interaction Energy (LIE). These relatively inexpensive methods offer accurate compound affinity ranking, but do not provide accurate binding free energy values.^{2–11} The second category includes explicit solvent methods such as thermodynamic integration (TI), free energy perturbation (FEP), Bennett's acceptance ratio method (BAR) , 12 lambda dynamics, 13,14 and weighted histogram analysis method (WHAM),¹⁵ which provide more accurate binding free energy values than implicit solvent methods. These explicit solvent methods have shown excellent accuracy in ligand binding affinity prediction across various therapeutic targets, including HIV protease, 16,17 HIV reverse transcriptase, 18 factor Xa, 7 fructose 1,6-biphosphatase, $^{19-21}$ and others.^{22–24} Among these explicit solvent methods. TI is probably the most common due to its simplicity in post processing (no molecular dynamics trajectory required), straightforward insertion of extra intermediate states for more accurate estimation, and intuitive integrand shape visualization to identify abnormal intermediate state transitions. It is also the best-supported explicit solvent method in the Amber Molecular Dynamics suite.

The explicit solvent methods, including TI, have been extremely computationally expensive, thus limiting their real world usage.^{25,26} There are several pioneering studies that have improved TI computational efficiency and accuracy by choosing the best performing integration method, 27.28 optimizing the simulation length, 29 sampling techniques, $30-32$ the number of transition steps, $33-36$ and the number of intermediate states^{7,37,38}. Nonetheless, these studies have mostly focused on solvation energy but not ligand binding free energy in proteins on a large scale. Moreover, the Amber Molecular Dynamics suite recently enabled TI in *pmemd*, which has been proven to be a more efficient MD engine than the older and slower *sander*,³⁹ but has not yet been extensively tested.⁴⁰ Since recent alchemical free energy studies suggest that prediction performance is system dependent, $41-43$ it would be useful to study the effects of algorithms, simulation length, the number of transition steps and intermediate states on TI ligand binding free energy in *F. tuleransis* FabI. The optimized TI protocol here will assist in our lead optimization campaign against *F. tuleransis* FabI (FtFabI). 2,44,45–47

Methods

Experimental Enzymatic Activity

The benzimidazole scaffold FabI inhibitors in this study and their activities are listed in Figure 1. The details of their IC_{50} & K_i experimental determination have been previously described.⁴⁷ The experimental binding free energy (G_{bind}) of these inhibitors was obtained from the experimentally determined K_i using Equation 1. T is room temperature (300K) and R is the ideal gas constant $(1.9872\times10^{-3} \text{ kcal K}^{-1} \text{ mol}^{-1})$.

 $\Delta Gbind = RT lnKi$ (1)

Complex Preparation

The protein-ligand binding conformations were obtained from the PDB codes, 3UIC (FtFabI: compound 138)⁴⁶, 4J3F (FtFabI: compound 56), and 4J1N.⁴⁷ The starting conformations of the FtFabI complex with compound 91, 135, 166, 177, 34, 52, 58, 09–12F, and 11–12F were obtained by removing and/or adding corresponding functional groups (highlighted in red in Figure 1) in a benzimidazole inhibitor from the above three crystal structures. The RESP charges for the ligands and the cofactor, NADH, were derived from the HF/6-31G* theory level in Gaussian 0.048 using the R.E.D. server.^{49,50} The General Amber force field $(GAFF)^{51}$ was assigned to ligands and the FF14SB force field was assigned to the protein using antechamber in Amber v14.⁵² The ligand and protein-ligand complexes were solvated in a 10 Å octahedral TIP3P water box with counter ions (Na^+ and Cl−) to neutralize the solvated systems.

Free Energy Calculation in the Three-Step Thermodynamic Integration

The TI simulations of pairs of similar ligands were separated into two parts: ligand transformation within the protein active site (G_{bound}) and ligand transformation in solvents (G_{free}). The binding free energy difference between these two similar ligands ($G_{(A\rightarrow B)}$) can be calculated from Equation 2:

 $\Delta\Delta G_{(A\rightarrow B)} = \Delta G_{\text{bindB}} - \Delta G_{\text{bindA}} = \Delta G_{\text{bound}} - \Delta G_{\text{free}}$ (2)

Each G_{bound} and G_{free} contains three steps. The first step is the charge removal of the ligand A region, which doesn't exist on ligand B. The second step is the vdW (vdW) transformation of the unique regions between ligands A and B. The third step is to assign the charge back to the ligand B region, which doesn't exist on ligand A. The Lennard-Jones Softcore potential (Equation 3) is activated in the second step to avoid any system instability as atoms disappear and appear,³³ where λ is a coupling parameter, r_{ab} is the atomic distance between two particles, ε is the Lennard-Jones potential well depth, σ is the distance where the two particles' intermolecular potential is equal to zero and α is the Lennard-Jones Softcore potential energy function curvature control parameter, which has previously been recommended to be α =0.5.³³

$$
V_{\text{softcore in vdW}} = 4\varepsilon (1 - \lambda) \left[\frac{1}{\left[\alpha \lambda + \left(\frac{r_{\text{ab}}}{\sigma} \right)^6 \right]^2} - \frac{1}{\alpha \lambda + \left(\frac{r_{\text{ab}}}{\sigma} \right)^6} \right] (3)
$$

In the six G_{bound} and G_{free} steps, each step is divided into 21 windows with different coupling parameters (λ), where λ =0 is the initial state and λ =1 is the final state. The energy in each step $($ G $)$ can be calculated using Equation 4 where the bracket represents the average of the potential energy of the studied system ($\sigma(\lambda)$) for the given λ value, which is calculated using the trapezoid integration method. The λ values in this study are listed in Table 1. Since each of the six steps has 21 windows, there are in total 126 windows in each ligand-pair three-step TI calculation, and each window includes 2 ns of molecular dynamics (MD) simulation production runs, making TI a computationally intensive method (252 ns MD simulation for each ligand-pair three-step TI calculation). The following "Simulation Details" list the MD simulation settings for each window.

$$
\Delta G = \int_{0}^{1} \left(\frac{\partial V(\lambda)}{\partial \lambda} \right) d\lambda \quad (4)
$$

Free Energy Calculation in the One Step Thermodynamic Integration

In the one step TI, the vdW and electrostatic transformation of the unique regions between ligands A and B both occur in the same step. Therefore, each G_{bound} and G_{free} contains only one step, and each step contains 21 windows, resulting in a total of 42 windows in each ligand-pair one-step TI calculation (82 ns MD simulation production runs). This could greatly reduce computational costs. However, the simultaneous electrostatic and vdW transformation events in the one step TI could result in high system instabilities, which is overcome in this study by activating both Lennard-Jones (Equation 3) and Coulomb Softcore potentials (Equation 5) simultaneously, 33 where q_a and q_b are electrostatic charges of transformed atoms in two ligands and β is the Coulomb Softcore potential energy function curvature control parameter, which has previously been recommended to be $\beta = 12 \text{ Å}^{2.33}$

Vsoftcore in electrostatic =
$$
(1 - \lambda) \frac{q_a q_b}{4 \pi \varepsilon \sqrt{\beta \lambda + r_{ab}^2}}
$$
 (5)

Simulation Details

The minimization was composed of the following four steps, following a protocol suggested in a recent TI study.¹⁷ The four step minimizations all shared the same settings in $2,500$ steps of steepest descent minimization, followed by 2,500 steps of conjugate gradient minimization with 10 Å non-bonded cutoffs. The only differences in each minimization step were the restraint force constant. Firstly, solutes (protein-ligand complexes or ligands) were restrained with a 500 kcal mol−1 Å−2 force constant while no restraints were put on solvents. In the second, third and fourth minimization steps, the restraint force constant on solutes was reduced from 10 to 2 to 0 kcal mol⁻¹ $\rm \AA^{-2}$, while solvents were allowed to move freely. Next,

a 100 ps density equilibration (NVT ensemble) was performed. The system was heated from 0 to 300K, and the Langevin temperature control was activated with a 2 ps−1 collision frequency, using 10 Å non-bonded cutoffs, the SHAKE algorithm and 2 fs time steps. The solutes were restrained with a 10 kcal mol⁻¹ $\rm \AA^{-2}$ force constant while solvents were allowed to relax. This was followed by a 100 ps constant pressure (1 bar) and temperature (300K) equilibration and a 2 ns production run (NPT ensemble) without any restraints on the system.

Accuracy and Error Measurement

The uncertainty in this study was estimated from the root-mean-square deviation (RMSD) in Equation 6, where G_{experimental} is described in the "Experimental Enzymatic Setting" part and Equation 1, and n is the number of ligand-pair transformations. The coefficient of determination (R^2) is used to describe the relationship between the experimental and predicted binding free energy differences of ligand-pairs. The standard error of the mean (SEM) is used for error estimate, as shown in Equation 7, where σ is the population standard deviation and n is the number of the samples in the population.

$$
RMSD = \sqrt{\frac{\sum (\Delta\Delta G \text{experimental} - \Delta\Delta G \text{calculated})^2}{n}} \quad (6)
$$

$$
SEM = \frac{\sigma}{\sqrt{n}} \quad (7)
$$

Results and Discussion

Comparison of Amber Algorithms and Transformation Steps in Accuracy

The TI calculation results using both old and new Amber MD engines, *sander* and *pmemd*, are listed in Table 2. Only four ligand-pair transformations (Figure 1, part 1) were extensively tested in the first part of this study due to the high computational costs of TI using *sander*, particularly with a large number of windows in a solvated protein-ligand complex system (about 32,000 atoms).

Recent studies have shown that some protein-ligand systems may require long TI simulations ($\frac{3.5 \text{ ns}}{2.5 \text{ ns}}$ production run per window) to reach convergence,^{29,32} while some other systems converge in a relatively shorter time frame (after 0.5~2 ns of production runs per window).7,53 Therefore, we first perform a 3.5 ns, one-step *pmemd* TI with 11 and 21 windows for four of the transformations, and plot the G_{bind (calculated- experimental)} and cumulative MD simulation length to check convergence, a simple convergence test recommended by the AMBER community and other studies^{7,53}, as shown in Supporting Figure 1. It can readily be seen that the predicted binding free energy difference exhibits no significant change after 1 ns of simulation length (within an uncertainty of 0.2 kcal/mol), in both 11 and 21 windows cases. However, it is obviously still possible that true convergence (global minimum) might only be reached after a few hundred ns of TI, which cannot be achieved within a reasonable time frame with current computational power. More efficient

TI protocols in the future, such as TI running on GPUs, might enable longer TI simulations to answer this question. In the current study, due to the goal of surveying multiple ligands with limited computational resources, we only perform 2ns of TI in different environment settings in this study. The plots of calculated G_{bind} (calculated- experimental) and cumulative MD simulation lengths suggest that all TI calculations using *sander*/*pmemd* and the one-step/three-step transformations in this study converged after 1 ns MD production runs (within an uncertainty of 0.2 kcal/mol), with the exception of the $135\rightarrow 138$ transformation (Figure 2). This result agrees with another recent study of the *Mycobacterium tuberculosis* InhA (*Mt*FabI): triclosan analogues system, where TI results converged after 600 ps of production runs.⁵³

It is known that TI converges poorly if large numbers of atoms or groups are involved in a transformation. Since the 135→138 transforms two hydrogen atoms into two methyl groups, it is not surprising that the $135\rightarrow 138$ transformation does not converge well except in the one-step TI using *pmemd*. In Table 2, RMSDs including and excluding the 135→138 transformation are both listed. In the following discussion, $RMSD_{all}$ represents all four transformations included RMSD, while RMSD_{excluded 135→138} means the 135→138 transformation is excluded.

In Table 2, both *sander* and *pmemd* in the three-step TI offer satisfactory prediction compared to experimental binding free energy (RMSDall ≤ 0.81 kcal/mol), while *pmemd* performs slightly better than *sander* in the three-step TI using 11 or more intermediate states (ΔRMSD ≤ 0.2~0.3 kcal/mol). This may be a consequence of *pmemd* allowing the initial and final states (λ values) to be 0 and 1 respectively, while *sander* only allows values very close to 0 and 1 (Table 2).40 Therefore, numerical integration in *pmemd* results requires no extrapolation and cancels its associated errors.

Similarly, the difference between *sander* and *pmemd* in the one-step TI using 11 or more intermediate states is trivial ($RMSD = 0.26$ kcal/mol). However, the one-step TI using either *sander* or *pmemd* (RMSD_{excluded 135→138 ranging from 0.76~1.29 kcal/mol) delivers} less agreement with experimental values than the three-step TI (RMSD excluded 135→¹³⁸ ranging from 0.32~0.80 kcal/mol). This may be a consequence of the one-step TI allowing simultaneous vdW and electrostatic transformations, and relying on both Lennard-Jones (Equation 3) and Coulomb Softcore potentials (Equation 5) together to enhance system stability. However, the two Softcore potentials in the one-step TI have only been tested in predicting solvation energy of small molecules³³. Therefore, the default setting of Lennard-Jones (Equation 3) and Coulomb Softcore potentials (Equation 5) in the one-step TI may need more optimization for this system. More details are discussed below in the "Optimization of the One-Step TI" section.

Accuracy Dependence on Simulation Length

Since computational expense is one of the major hurdles for thermodynamic integration and other alchemical free energy calculation methods (FEP, BAR, etc.), shortening the simulation lengths and increasing the computational efficiency will be of high interest. Because the G_{bind(experimental-calculated)} converge after 1 ns of simulations (Figure 2) (within an uncertainty of 0.2 kcal/mol, and excepting the 135→138 transformation), it is of

interest to see if the TI accuracy is maintained using 1 ns MD simulations; the results are listed in Table 3. In Table 2 $\&$ 3, it is clearly shown that TI using 1 ns MD simulations has slightly lower RMSD values than 2 ns MD simulations in most circumstances (excluding the non-converged 135→138 transformation), with $RMSD_(1ns-2ns)$ ranging from -0.14 to 0 kcal/mol, (Table 3, the $RMSD$ _(1ns–2ns) column). This result suggests that TI using 1 ns MD simulations offers sufficient sampling and accuracy. On the other hand, if only one trajectory is used for each window, the extra 1 ns simulation of TI using 2 ns MD simulation may not sample more useful conformations, but may amplify inaccuracies in the force field and slightly degrade the prediction results, as suggested in prior studies.2,7

Effect of the Number of Intermediate States on Accuracy

TI calculations with six intermediate states provide the best agreement with experimental results (lowest RMSDexcluded 135→138 values) for both the *sander* three-step/one-step TI and the *pmemd* three-step TI using either 1 or 2 ns MD simulations (Tables 2 & 3). Using *pmemd* for the one-step TI is the only circumstance where a larger number of intermediate states offers a better performance (lower RMSD values). However, 21 intermediate states (including all four transformations) only provides 0.18 kcal/mol lower RMSD values than 11 intermediate states in the *pmemd* one-step TI, but with almost twice the computational cost. This does not justify the usage of large numbers of intermediate states. On the other hand, 6 intermediate states in the *pmemd* one-step TI yields an unsatisfactory RMSD_{excluded 135→138} of 1.29 kcal/mol (with a cutoff of ~1 kcal/mol), while 11 and 15 intermediate states provides a broader line accuracy $(RMSD_{all} = 1.07$ and 0.93 kcal/mol correspondingly). Therefore, 11 or 15 intermediate states seem to offer the best balance between predictive accuracy and efficiency in the *pmemd* one-step TI.

Effect of Amber Algorithms, Transformation Steps, Number of Intermediate States and Simulation Length on Efficiency

If one averages the speed of *pmemd* and *sander* over all intermediate states and calculates their relative efficiency using Equation 8^{40} , *pmemd* provides a calculation 3.1 times faster than *sander*, similar to the previous reports by the *pmemd* TI developers (previously reported: *pmemd* about 2.9 times faster than *sander*).40 Moreover, *pmemd* has several additional advantages: (1) *sander* scaling performance is optimal only if the number of cores is a power of two, while *pmemd* has no such limitation. This will allow TI calculations to be more efficient in cluster machines where the number of cores per node is not necessarily a power of 2;40 (2) *sander* only allows minimization of a vdW transformation step on two cores (in both the one-step and three-step TI) while *pmemd* does not have such a limitation.40 Since TI equilibrium and production runs immediately after a minimization require more than two cores to finish a TI job in a reasonable time, users can request the same number of cores in TI minimization, equilibrium and production runs in *pmemd* for convenience;40 and (3) *pmemd* is more scalable to larger numbers of cores than *sander*. 40 Putting all these factors (queue times, etc.) together, TI calculations in *pmemd* are about 4–5 times faster than in *sander*, using the University of Illinois at Chicago (UIC) Extreme Computing machine, with 16 Intel Xeon E5-2670 2.6 GHz CPUs per node and QDR infiniband communication between nodes.

relative efficiency= $\frac{speed \ in \ pmemd \ (\frac{ns}{day})}{speed \ in \ sender \ (\frac{ns}{day})}$ (8)

TI efficiency decreases linearly with larger numbers of transformation steps, intermediate states and longer simulation length: the one-step TI is three times faster than the three-step TI (assuming both cases converge); 11 intermediate states is about twice as efficient as 21 intermediate states, and TI using 1 ns MD simulations is twice as fast as 2 ns. In this case, the one-step TI using *pmemd*, 11 intermediate states and 1 ns simulations would be the most efficient method, considering $RMSD_{\text{excluded 135}\rightarrow138}$ values closer to 1 kcal/mol (Table 3). Using 96 Intel Xeon E5-2670 2.6 GHz CPU cores with QDR infiniband between nodes for the 11 windows one-step TI correspondingly, one pair of ligand TI calculations can be finished in 10 hours. However, the one-step TI is not as accurate as the three-step TI as mentioned above (Table 3). If the *pmemd* three-step TI calculation using 6 intermediate states and 1 ns MD simulations is implemented using 96 Intel Xeon E5-2670 2.6 GHz CPUs on the UIC Extreme machine, it requires 13.8 hours excluding any queue time. Since using a large number of cores might prolong the queue time on a cluster machine, and might not be easily available, there is strong interest to optimize the efficient one-step TI protocol to improve its accuracy.

Optimization of the pmemd One-Step TI

In a one-step TI calculation, the α and β parameters in Equation 3 & 5 are the Lennard-Jones and Softcore potential energy function curvature control parameters, respectively. These two parameters have thus far only been explored in the solvation energies of small molecules.³³ Previous solvation energy studies suggest that decreasing α from 0.5 to 0.2 might improve the accuracy.^{33,52} Therefore, we initially tested α values from 0.6 to 0.2, decrementing by 0.1, while keeping β constant at 12 $\rm \AA^2$ (Table 4).

In Table 4, the RMSDall values are almost all larger than 1 kcal/mol across various α values, ranging from 0.93 to 1.90 kcal/mol, since the predicted G_{bind} values of the 135 \rightarrow 166 transformation all significantly overestimated the experimental G_{bind} values (by 1.26~2.26 kcal/mol). If the 135→166 transformation is excluded from the RMSD calculation, as shown in the rightest column of Table 4, all $RMSD_{excluded}$ 135 \rightarrow 166 values are below 1 kcal/mol across various α values.

The one-step TI results converged using $\alpha = 0.5, 0.4,$ and 0.3, together with fixed $\beta = 12$ (\AA^2) (if 0.2 kcal/mol error is allowed), as shown in Supporting Figure 2. These three settings also give comparably low RMSD values (particularly if the 135→166 transformation is excluded), while $\alpha = 0.3$ gives the lowest all-transformations-included RMSD (0.93) kcal/mol in 11 windows). $\alpha = 0.2$ doesn't provide converged results (Supporting Figure 2). Using α = 0.6 was not recommended in the initial study,³³ and our data also suggests that the one-step TI with $\alpha = 0.6$ doesn't converge in either 6 or 11 windows using 1 ns MD simulations (Supporting Figure 2). Therefore, $\alpha = 0.3$ seems to be the best value for the cases studied here. However, the predicted G_{bind} value of the 135 \rightarrow 166 transformation still deviates excessively from the experimental value using $\alpha = 0.3$ and $\beta = 12$ (\AA^2). Since the β value controls the Coulomb Softcore potentials (Equation 5), it was of interest to see if

fine-tuning the β value with α =0.3 could offer better performance, particularly for the 135→166 transformation.

The results of incrementing the β value by 3 Å², from 12 to 21 Å², while keeping α constant at 0.3, are listed in Table 4 and Supporting Figure 3. Among the various β values, only $β =$ 12 and 18 Å² provide converged G_{bind} of all transformations. Particularly, $β = 18 Å²$ and $\alpha = 0.3$ using 11 windows offers the lowest all-transformation-included RMSD (0.79) kcal/mol in 11 windows), while the G_{bind} of all transformations converged (Supporting Figure 3). The setting of $β = 18 \text{ Å}^2$, $α = 0.3$ and 11 windows also offers the best accuracy for the 135 \rightarrow 166 transformation. Therefore, the one-step *pmemd* TI with α = 0.3 and β = 18 (\AA^2) using 11 windows seem to be the best one-step TI Softcore potential settings for our FabI-benzimidazole system.

The one-step TI, regardless of various settings, encounters difficulties in the 135→166 transformation. Even though the $β = 18$ $Ų$ and $α = 0.3$ combination in the one-step TI provides one of the lowest $RMSD_{all}$ and best converged prediction results for the 135 \rightarrow 166 transformation (1.84 kcal/mol), it is still 1.08 kcal/mol over-estimated from the experimental value. The $135\rightarrow 166$ transformation exchanges a hydrogen atom for a methyl group at the 2 position of the benzimidazole ring (Figure 1). Therefore, it would be expected that the vdW interaction is the primary contribution in this transformation. However, the nitrogen atom at the 3 position of the benzimidazole ring forms a key hydrogen bond interaction with the FabI Tyr156 and the hydroxyl group of the NADH nicotinamine ribose (Figure 3). Since the methyl group could attract electrons from the nitrogen atom, the 135→166 transformation is believed to affect not only the vdW interaction, but also the electrostatic distribution of the nitrogen atom, and weaken the key hydrogen bonds. Since vdW radius and charge transformations occur simultaneously in the one-step TI, the one-step TI might not offer an accurate estimate on the 135→166 transformation as the three-step TI: the *pmemd* three-step TI using 6 windows can offer a significantly better and converged prediction for the 135→166 transformation (1.06 kcal/mol), only 0.3 kcal/mol over-estimated (Table 3). Hence, if a highly accurate prediction is required for the modification of the 2 position on the benzimidazole ring, the *pmemd* three-step TI using 6 windows would be recommended. If only a quick estimate is required, the *pmemd* one-step TI using 11 windows, $α = 0.3$ and β $= 18 \text{ Å}^2$, can still capture the behaviour of the 2 position modification of the benzimidazole ring with borderline accuracy.

Further Validation and Medicinal Chemistry Perspective

The additional three ligand-pair transformations shown in Part 2 of Figure 1⁴⁷ were tested to further validate the best performing and the most efficient one-step *pmemd* TI ($\alpha = 0.3$, $\beta =$ 18 \AA^2 , 11 windows) and the three-step *pmemd* TI (6 windows), both using 1 ns MD simulations. The results are shown in Table 5 and Figure 4.

In the three-step *pmemd* TI with 6 windows calculations, the 34→58 transformations do not converge, as shown in Figure 4a. Therefore, in Table 5, the RMSD including all transformations is on the high end (0.94 kcal/mol) and the coefficient of determination is low ($R^2 = 0.48$) due to the 135→138 and non-converged 34→58 outlier transformations. When the RMSD_{all} was calculated including the $135 \rightarrow 138$ and $34 \rightarrow 58$ transformations

results from the one-step *pmemd* TI in 11 windows (seven transformations), the result improved significantly (RMSD_{all} = 0.48 kcal/mol and $R^2 = 0.83$). On the other hand, the one-step *pmemd* TI using 11 windows and 1 ns MD simulations converged for all seven transformations, while the 135→138 transformation didn't converge in the one-step *pmemd* TI using 6 windows. The one-step *pmemd* TI using both 6 and 11 windows offered quite satisfactory results (RMSD = 0.75 and 0.66 kcal/mol). Moreover, the $135\rightarrow 166$ transformation has been shown to be difficult for the one-step *pmemd* TI, as discussed in the previous section. If the one-step *pmemd* TI result is re-calculated using the 135→166 transformation result from the three-step *pmemd* TI in 6 windows, the RMSD of the new one-step *pmemd* TI can be as low as 0.52 and 0.53 kcal/mol for 6 and 11 windows, respectively.

The TI results here are also consistent with our structure-activity relationship (SAR) (Tables 5 & 6). The in-house crystal structure (pdb code: 3UIC) suggests that the distance between the *para*-chloride in compound 91 and the backbone carbonyl group of Pro154 is 3.49 \AA ,⁴⁶ slightly outside the halogen bond distance range (carbonyl to chloride: $3.00 - 3.40 \text{ Å}$), which is calculated in the previous perspective studies (Figure 3).^{54,55} However, the halogen bond distance range in carbonyl to bromide is slightly larger $(3.00 - 3.50 \text{ Å})$, and the center of *para*-bromide in compound 177 and the backbone carbonyl group of Pro154 is still 3.49 Å. Therefore, the in-house structural study suggests that the *para*-chloride and *para*- bromide in compound 91 and 177 might form a mixture of halogen bond and vdW interactions in this hydrophobic pocket.46 In both of our in-house SAR and TI calculation results, the *para*chloride to bromide substitution in the $91 \rightarrow 177$ transformation improves the binding affinity (Table 6, $G_{\text{exnt}} = -1.27$ (kcal/mol), $G_{\text{TT}} = -0.87 \pm 0.05$ (kcal/mol)). The TI result also suggests that the binding free energy difference in the $91\rightarrow 177$ transformation is mostly from vdW interactions (83%) with minor electrostatic interactions (17%), as shown in Table 6. Because a halogen bond consists primarily of electrostatic interactions,54 the 17% of electrostatic interactions here might support the concept of a halogen bond and vdW interactions mixture, where vdW interactions are still the major ones. It has been reported that the traditional biomolecular modeling force fields might result in up to 1–2 kcal/mol error in halogen bonding calculations.⁵⁶ This might explain why the G_{TT} of 91 \rightarrow 177 transformation in this study deviates -0.4 ~ -0.8 kcal/mol from the corresponding G_{exnt} . The recently customized force fields for halogen boding, such as the positive extra-point approach in the AMBER general force field (GAFF)^{57,58} and the OPLS-AA⁵⁶ force field, and the polarizable ellipsoidal approach⁵⁹ compatible with the AMBER GAFF, or even the computationally expensive density function theory approach⁶⁰ might provide more accurate insights of the potential halogen bonds between FabI benzimidazole inhibitors and FabI, a well-known halogen bond favoring enzyme,⁵⁴ but comparative studies of halogen bonding potentials were beyond the scope of this study, and thus we simply note the potential uncertainty.

Moreover, the TI data agree with the experimental results that the *meta*-chloride (91 \rightarrow 135) and *meta*-methyl (52→56) substitutions are also binding favorably because the *meta*chloride and methyl provides hydrophobic interactions to the FabI hydrophobic region comprised of the Ile200 and Leu99 side chains. Comparing to the *meta*-chloride and *meta*-

methyl, the TI result in the 09–12F \rightarrow 11–12F transformation shows a positive G_{step2} (0.49 kcal/mol in Table 6), and indicates that the methoxy group induces unfavorable binding free energy from a steric effect. The summation of the G_{step1} and G_{step3} in the 09–12F \rightarrow 11–12F transformation is positive as well (0.33 kcal/mol), which is a bindingunfavorable G_{electrostatic}, possibly from introducing a more polar methoxy group in a lipophilic region. These observations are consistent with our previous SAR and structural biology analysis (pdb code: 4J3F and 4J4T).⁴⁷

On the other hand, the 5 and 6 positions of the benzimidazole ring are within an empty hydrophobic pocket (Figure 3). Here the G_{bind} of the 135 \rightarrow 138 transformation is highly negative, −3.10 kcal/mol (Table 6), suggesting that introducing any hydrophobic group, two methyl groups here as an example, favors the binding. Moreover, the G_{step2} of the $135 \rightarrow 138$ transformation contributes the most to the G_{bind} , indicating that the hydrophobic vdW interactions here play a key role (Table 6). In contrast, a more polar substitution in this hydrophobic pocket, such as the $34 \rightarrow 58$ transformation, reduces the binding affinity (Table 6).

The positive G_{step2} of the 135→166 transformation (1.85 kcal/mol in Table 6) contributes the most to the G_{bind} in the 135 \rightarrow 166 transformation (1.06 kcal/mol in Table 6), indicating that a steric clash of the methyl group on the 2 position of the benzimidazole ring lowers the binding affinity, as previously noted (pdb code: 3UIC).⁴⁶ Moreover, our previous structure metabolic stability relationship (SMR) analysis also determined that a methyl group or a hydrogen bond acceptor substitution in the 2 position of the benzimidazole ring compromises the metabolic stability, limiting substitution options at this position.⁴⁵

Interestingly, our prior analysis has shown that the QM-MM/GBSA method using 2,400 frames evenly extracted from 6 ns molecular dynamic simulations trajectories, the GB_{neck2} method, the PM3 Hamiltonian, and the mbondi2 effective radii setting, can rank the benzimidazole binding affinity accurately $(R^2$ between predicted and experimental binding free energy is equal to 0.88).² However, QM-MM/GBSA fails to quantify the binding free energy differences between two similar benzimidazole ligands, since the RMSD including all seven transformations using QM-MM/GBSA is as high as 3.00 kcal/mol (Table 5). If the inaccurate entropy calculation results from our former study 2 are excluded and only the enthalpy differences between two similar benzimidazole ligands are included into the RMSD calculation, the RMSD including all seven transformations using QM-MM/GBSA is still not satisfactory ($\text{RMSD}_{all} = 2.28 \text{ kcal/mol}$, Table 5). Former studies also suggested that implicit solvent methods, MM/PBSA and (QM−)MM/GBSA, take even more computational resources than explicit solvent methods (TI, FEP, BAR, etc.) in order to reach a converged and satisfactory quantification of binding free energy differences.⁷ Therefore, implicit solvent methods are more suitable for binding affinity ranking rather than binding free energy difference quantification.

Conclusions

In this study, we have shown TI to be affordable for a real world, large scale prediction. The one-step *pmemd* TI using 1 ns MD simulations and 6 windows can be as efficient as such implicit solvent methods as QM-MM/GBSA. The one-step *pmemd* TI using 1 ns MD simulations and 6 windows can finish in 5 hours for one protein-ligand binding pair transformation using 96 Intel Xeon E5-2670 2.6 GHz CPUs on the UIC Extreme Computing machine. In comparison, our former study suggests that $OM-MM/GBSA$, using the GB^{neck2} method, the PM3 Hamiltonian, the mbondi2 radii setting, and 2,400 frames extracted evenly from 6 ns MD simulations trajectories, requires 4.5 hours.² Besides the improvement in TI efficiency, TI offers higher accuracy in prediction of binding free energy differences between two similar ligands than does QM-MM/GBSA (RMSD 0.75 kcal/mol versus 3.07 kcal/mol). This result is highly encouraging as alchemical free energy calculation methods, such as TI, have been notorious for their slow predictive speed. It usually ended up requiring longer real world time than a synthetic chemist making a small modification on a certain scaffold. However, as the advance of the methodology and protocols highlighted in the former and current studies, universities and pharmaceutical companies equipped with small or medium size computer clusters can utilize TI to predict large scale putative ligand transformations and provide useful insights for a drug discovery team.

One of the major TI speed improvement comes from the TI implementation in a newer and faster Amber MD engine, *pmemd*, in April 2014.⁴⁰ This study has shown in a larger scale than the former study that the *pmemd* TI can be significantly more efficient than TI implemented on the older and slower Amber MD engine, *sander*, while the *pmemd* TI still maintains similar accuracy (Tables 2 & 3). The *pmemd* TI is shown to be 3.1 times faster than *sander* TI using the conditions of this study. Moreover, *pmemd* scales better than *sander* TI, consistent with the former study. *Sander* also requires the number of cores to be a power of two to reach its optimal speed, while *pmemd* has no such limitation. This allows *pmemd* to fully maximize its performance using a machine where the number of cores in a node is not a power of two. Lastly, the *sander* TI only allows minimization to be run on two cores when activating Softcore potentials, while the following equilibration and production runs still require a larger number of cores to finish computation jobs in a timely manner. This complicates job submission and might prolong the job queue time. Briefly, our experience suggests that the *pmemd* TI might be 4–5 times faster than the *sander* TI, including the above factors and the associated queue time, etc. Other TI efficiency improvements included reducing the MD simulation lengths from 2 to 1 ns (Table 2–3) and the number of windows from 21 to 6 (Table 2–5) without compromising the convergence and accuracy of results, consistent with the former pioneering studies. 7,33–37

Moreover, we have tested various vdW and Coulomb Softcore potential controlling parameters (α and β values) in the one-step TI in a protein-ligand system for the first time (Tables 4 and 5). The results suggest that the one-step *pmemd* TI using 6 windows can offer convergence and accuracy comparable (RMSD = 0.75 kcal/mol) to the three-step *pmemd* TI (RMSD = 0.83 kcal/mol) when α is equal to 0.3 and β is equal to 18 Å². Moreover, implementation of the one-step TI can offer three times faster speed than the traditional three-step TI. However, the one-step *pmemd* TI cannot provide as high accuracy prediction

in the 135→166 transformation as the three-step *pmemd* TI. The hydrogen at the 2 position of the benzimidazole ring transforms into a methyl group in the $135\rightarrow 166$ transformation. This 2 position methyl group is believed to attract electrons from the 3 position nitrogen atom of the benzimidazole ring, which forms key hydrogen bond interactions with the enzyme and the NADH cofactor (Figure 3). Therefore, the simultaneous vdW radius and charge transformations in the one-step TI might not be as suitable as the three-step TI for this special case. The three-step *pmemd* TI using 6 windows and 1 ns MD simulations would be encouraged in any future TI prediction on this 2 position modification (Table 5). Moreover, the one-step *pmemd* TI using 6 windows might not be ideal for a larger modification such as the $135\rightarrow 138$ transformation (two hydrogen atoms transformed into two methyl groups) due to the non-converged result (Figure 4). In such a case, implicit solvent methods might be better to quickly rank the binding affinities of more distant molecules. If a more accurate quantification for a larger modification is required, the threestep *pmemd* TI using 6 windows or the one-step *pmemd* TI using 11 windows, which offer the converged 135→ 138 transformation results, might be better than the *pmemd* one-step *pmemd* TI using 6 windows. Lastly, except for the special cases in the 135→ 138 and 135→ 166 transformations, the one-step *pmemd* TI using 6 and 11 windows achieved almost identical accuracy (RMSD = 0.52 and 0.53 kcal/mol). As the TI with 11 windows takes almost twice as long as TI using 6 windows, the one-step *pmemd* TI using 6 windows and 1 ns MD simulations will be the preferred choice for our lead optimization campaign against *F. tuleransis* FabI.

Lastly, the TI results here also provide benzimidazole structure-activity relationship insights in the FtFabI active site and also suggest that the *para*-halogen in benzimidazole inhibitors might form a weak halogen bond with FtFabI. Future study using customized force fields for halogen boding $56-59$ or even the computationally expensive density function theory approach⁶⁰ might provide more details of the potential halogen bond between FabI benzimidazole inhibitors and FabI, which is a well-known halogen bond favoring enzyme.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

This work was supported in part by National Institutes of Health Grant U01 AI077949. Pin-Chih Su was financially supported by the American Heart Association (AHA) pre-doctoral fellowship, 13PRE-14800030. Computational resources were kindly provided by the Texas Advanced Computing Center (TACC), Lonestar cluster at the University of Texas at Austin under the XSEDE Teragrid Grant TG-MCB090168 to MEJ, and by the Extreme Computing Machine at the University of Illinois at Chicago. We thank the amber community ([http://](http://archive.ambermd.org/) [archive.ambermd.org/\)](http://archive.ambermd.org/) and Drs. Kirk E. Hevener, Paul Gasper, Paulius Mikulskis, Levi Pierce, William Sinko and Jason Swails for helpful discussions.

Abbreviations

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Figure 1.

The eleven benzimidazole scaffold FtFabI inhibitors in this study. The TI transformation groups are highlighted in bold and indicated in arrows. Part 1 is the benchmark set and part 2 includes more compounds for the test.

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Figure 2.

Plots of calculated $G_{bind(calculated} experimental)$ (kcal/mol) vs. cumulative MD simulation lengths using 11 windows

Figure 3.

The binding mode of the compound 135 from the in-house crystal structure (pdb code: 3UIC). The nitrogen atom at the 3 position of the benzimidazole ring forms key hydrogen bonds with the NADH nicotinamide ribose (truncated for clarity) and Tyr156. The 5 and 6 positions of the benzimidazole ring fall into a lipophilic cavity, formed by the Ile91, Ala92, Phe93, Ala94, Pro95, and Ala197 side chains. The para-chloride might form a weak halogen bond with the carbonyl backbone of Pro154, as discussed in the "Further Validation and Medicinal Chemistry Perspective" section. The meta-chloride is in a hydrophobic pocket formed by the Leu99 and Ile200 side chains.

Figure 4.

Plots of calculated $G_{bind(experimental-calculated)} (kcal/mol) vs. cumulative MD simulation$ lengths using the *pmemd* three and one step TI ($\alpha = 0.3$, $\beta = 18$ (\AA^2)).

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Table 1

The Intermediate States (λ) in This Study λ) in This Study The Intermediate States (

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Table 2

Calculated and Experimental G_{bind} (kcal/mol) of Benzimidazole Inhibitors in FtFabI using 2 ns MD simulations Calculated and Experimental α_{bind} (kcal/mol) of Benzimidazole Inhibitors in FtFabI using 2 ns MD simulations

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 b RMSD excluding the non-converged 135 \rightarrow 138 transformation. b RMSD excluding the non-converged 135

 ${}^{\prime}$ The error estimate using the standard error of the mean in Equation 7. *c*The error estimate using the standard error of the mean in Equation 7.

 \rightarrow 138 transformation.

l.

Table 3

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Calculated and Experimental G_{bind} (kcal/mol) of Benzimidazole Inhibitors in FtFabI using 1 ns MD simulations Calculated and Experimental α (kcal/mol) of Benzimidazole Inhibitors in FtFabI using 1 ns MD simulations

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 b RMSD excluding the 135 \rightarrow 138. b RMSD excluding the 135 \rightarrow 138.

 $RMSD$ (excluding the 135 \rightarrow 138) in 1 ns MD simulation trajectories minus RMSD (excluding the non-converged 135 \rightarrow 138) in 2 ns MD simulation trajectories. *c*RMSD (excluding the 135→ 138) in 1 ns MD simulation trajectories minus RMSD (excluding the non-converged 135→ 138) in 2 ns MD simulation trajectories.

 $d_{\mbox{\scriptsize T}}$
the error estimate using the standard error of the mean in Equation 7. $d_{\text{The error estimate using the standard error of the mean in Equation 7.}$

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Table 4

Calculated and Experimental G_{bind} (kcal/mol) of Benzimidazole Inhibitors in FtFabI using the pmemd one-step TI and 1 ns MD simulations Calculated and Experimental ΔΔGbind (kcal/mol) of Benzimidazole Inhibitors in FtFabI using the *pmemd* one-step TI and 1 ns MD simulations

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 \rightarrow 166 transformation *c*The error estimate using the standard error of the mean in Equation 7.

 ${}^{\prime}$ The error estimate using the standard error of the mean in Equation 7.

Calculated and Experimental

Table 5

*a*Experimental G values. Experimental G values. *b* α in Equation 3 = 0.3, β in Equation 5 = 18 (Å²). The QM/MM-GBSA results use 2,400 frames evenly extracted from a 6 ns molecular dynamic simulations trajectories, the GBneck2 method, the PM3 Hamiltonian, and mbondi2 effective radii setting *c*The QM/MM-GBSA results use 2,400 frames evenly extracted from a 6 ns molecular dynamic simulations trajectories, the GBneck2 method, the PM3 Hamiltonian, and mbondi2 effective radii setting A). $A - T S$ B)- $(H$ B -T S \rightarrow B)=(H) from our previous study. G(A *d*The QM/MM-GBSA results use 2,400 frames evenly extracted from a 6 ns molecular dynamic simulations trajectories, the GBneck2 method, the PM3 Hamiltonian, and mbondi2 effective radii setting from our previous study. H(A \rightarrow B)= H $B-$ H A.

 $^{\prime}$ The error estimate using the standard error of the mean in Equation 7. *e*The error estimate using the standard error of the mean in Equation 7.

Gcalculated. R^2 is the coefficient of determination between G_{exp} and $G_{\text{calculated}}$ $\mathrm{G}_{\mathrm{exp}}$ and f_{R} ² is the coefficient of determination between

 ${}^g\mathbf{C}$ alculated including all transformations. *g*Calculated including all transformations.

*h*Calculated including the 135 $h_{\text{Calculated including the 135}\rightarrow138}$ and 34+58 transformations results from the one-step *pmemd* TI using 11 windows. →58 transformations results from the one-step *pmemd* TI using 11 windows.

 t calculated including the 135-+166 transformation result from the three-step pmemd TI using 6 windows. →166 transformation result from the three-step *pmemd* TI using 6 windows. *i*Calculated including the 135

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 ${}^b\!{\rm The}$ error estimate using the standard error of the mean in Equation 7. b^b The error estimate using the standard error of the mean in Equation 7.

 c GStep1+ GStep2+ GStep3= GTI. Any slightly unmatched values are due to rounding error. *c*ΔΔGStep1+ΔΔGStep2+ΔΔGStep3=ΔΔGTI. Any slightly unmatched values are due to rounding error.