Affordable Ab Initio Path Integral for Thermodynamic Properties via Molecular Dynamics Simulations Using Semiempirical Reference Potential

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Abstract

Path integral molecular dynamics (PIMD) is becoming a routinely applied method for the incorporation of the nuclear quantum effect in computer simulations. However, direct PIMD simulations at an *ab initio* level of theory are formidably expensive. Using the protonated 1,8-bis(dimethylamino)naphthalene molecule as an example, we show in this work that the computational expense for the intra-molecular proton transfer between the two nitrogen atoms can be remarkably reduced by implementing the idea of reference-potential methods. The simulation time can be easily extended to a scale of nanosecond while maintaining the accuracy on an *ab initio* level of theory for thermodynamic properties. In addition, the post-processing can be carried out in parallel on massive computer nodes. A 545-fold reduction in the total CPU time can be achieved in this way as compared to a direct PIMD simulation at the same *ab initio* level of theory.

TOC Graphic



Introduction

Hybrid QM/MM is now the method of choice for the studies of enzymatic reactions and chemical reactions in the condensed phase.^{1–13} However, the application of QM/MM methods is often plagued with extremely poor computational scaling of the *ab initio* QM methods, as well as the long time scales of molecular dynamics propagation that are usually required before any essential dynamic processes for the degrees-of-freedom (DoF) orthogonal to the boosted one can be observed.¹⁴ Furthermore, exploring the nuclear quantum effect (NQE), such as tunneling, nuclear delocalization phenomena, and zero-point energy of molecules, gains in popularity over the years.^{15–22} One of the most appealing approaches to incorporating NQE is path integral molecular dynamics (PIMD).²³ PIMD is based on the isomorphism to a pproximately transform the representation of quantum effect in single-particle systems into a classical system with discrete finite number of pseudo-particles (or beads) along a cyclic path.²⁴ Being one of the most commonly used simulation methods, PIMD can be used to obtain thermostatistical equilibrium properties and dynamic properties, with free energy profiles of reactions and reaction rate coefficients as two representative examples.^{25–28}

However, applications of PIMD simulations in the studies of chemical reactions of complex systems are extremely demanding. On the one hand, PIMD requires P times more computational time than that of the classical molecular dynamics (MD), where P is the number of beads, onto which each quantum particle is mapped. P determines the convergence of PIMD simulations, and it needs to satisfy $P > \hbar \omega_{max}/k_BT$, where ω_{max} is the maximal vibrational frequency of the system. P surges as ω_{max} increases or T decreases. It is thus computational expensive to use PIMD to study a reaction in a sufficiently long timescale at an acceptable accuracy with convergence-ensured number of beads. To reduce the computational cost, some progresses have been achieved. Tuckerman et al combined a noncanonical transformation on the quadratic part of the action with multiple time scale integration techniques, and proposed a very efficient algorithm.²⁹ Markland and Manolopoulos proposed an approach to reduce the computational effort by separating the short-range interaction from the longrange one.³⁰ Cheng et al proposed the multiple-timestep molecular dynamics (MTS-MD) algorithm to accelerate the propagation by dividing the force into slowly oscillating part and quickly varying component,³¹ but the former factor is still the efficiency bottleneck. Large integration time step can also be made possible by applying proper transformations, so the analytic integration over the high-frequency modes is allowed.³² After the transformation, the number of the beads can be reduced via ring-polymer contraction, in which some highest normal modes can be ignored.^{33–35} Marsalek and Markland proposed a ring polymer contraction approach that can dramatically reduce the computational cost of PIMD at an *ab initio* level.³⁶ On the other hand, the accessible simulation time is further limited when it is necessary to use high-level electronic structure methods such as post-Hartree-Fock theories and density functional theory (DFT). Approximated levels of theory, such as semi-empirical (SE) methods, can improve computational efficiency and allow sufficient exploration in the phase space for systems in condensed phase. However, these methods are crude in the treatment of electronic structures, which may lead to inexact results for certain physical properties.

In addition, ergodicity in the configurational space is critical for the convergence of the simulated macrostate properties. Enhanced sampling methods, such as umbrella sampling (US),³⁷ adaptively biased molecular dynamics (ABMD),³⁸ and metadynamics,^{39,40} are now frequently employed to boost one or two DoF and thereby accelerate the reaction. For the orthogonal DoF, the exploration can still be hindered by hidden barriers, and a ns-timescale simulation can be inevitable. Besides, length of the simulations determines the effective number of samples, because independent and identically distributed (i.i.d.) samples are required for the calculations of ensemble averages. For simulations in aqueous solutions, the energy correlation time is on a scale around 1 ps. If the samples are saved too frequently, sampling inefficiency must be considered.⁴¹ Affordable studies are limited to relatively simple systems,⁴² low levels of theory,⁴³ or with the aid of artificial intelligence.⁴⁴

Therefore, it is desirable to develop a practical method for the study of thermodynamics properties based on PIMD that can dramatically reduce the computational expense while maintain the accuracy. The multistate thermodynamic perturbation (MsTP) is the method of choice, of which the efficiency and reliability has been examined by Li et al. in an early study of some model reactions.⁴⁵ MsTP is a variant of the reference-potential method, in which the ensemble averages of any time-independent physical properties at a high level of theory are obtained indirectly from simulations at a lower level of theory. With further improvement,^{46–48} this method is becoming more robust for the studies of chemical processes in the condensed phase.

In the current work, we combine PIMD with the reference potential method for the first time and demonstrate its application in the study of the intramolecular proton transfer in the protonated 1,8-bis(dimethylamino)naphthalene (DMANH) molecule. The free energy profile at the PIMD/BLYP-D3/6-31G(d)/MM level of theory along the proton transfer pathway was calculated leveraging a more efficient sampling at the PM6/MM level. A 545-fold enhancement in the computational efficiency was achieved as compared to a direct PIMD simulation at the same *ab initio* level of theory.

Theory

The partition function of a system with N distinguishable particles is defined as,⁴⁹

$$Z_P(\beta) = \mathcal{N} \int \mathrm{d}^{NP} \mathbf{p} \int \mathrm{d}^{NP} \mathbf{x} \, e^{-\beta \hat{H}_p(\mathbf{x}, \mathbf{p})},\tag{1}$$

where $\beta = 1/k_B T$, \mathcal{N} is the total normalization function, \mathbf{x} represents the position of particles, and \mathbf{p} the momenta conjugate to \mathbf{x} . The isomorphic primitive Hamiltonian operator $\hat{H}_p(\mathbf{x}, \mathbf{p})$ of this N-atom P-bead cyclic model is

$$\hat{H}_{p}(\mathbf{x},\mathbf{p}) = \sum_{i=1}^{P} \left\{ \sum_{n=1}^{N} \left[\frac{\mathbf{p}_{n}^{i^{2}}}{2\widetilde{m}_{n}^{i}} + \frac{1}{2} m_{n} \omega_{p}^{2} (\mathbf{x}_{n}^{i+1} - \mathbf{x}_{n}^{i})^{2} \right] + \frac{1}{P} U(\mathbf{x}_{1}^{i}, \cdots, \mathbf{x}_{N}^{i}) \right\}_{\mathbf{x}_{n}^{i+1} = \mathbf{x}_{n}^{i}}, \quad (2)$$

under the constraint $\mathbf{x}_n^{i+1} = \mathbf{x}_n^i$. This quantum Hamiltonian operator is made up of P group of beads (also known as replicas or time-slices), and each forms a classical representation of the original system. Beads of each atom are connected by harmonic potentials. In this way, a P-membered classical "necklace" model is constructed, and the simulation of quantum systems is transformed into an expanded classical calculation. m_n is the mass of the particle, U is the potential energy, \widetilde{m}_n^i and \mathbf{p}_n^i are the fictitious mass of the *i*th bead of the *n*th particle and its corresponding momentum. This fictitious mass can be set to an arbitrary value, because this term disappears in the thermodynamical statistical average. The $\omega_p = \sqrt{P}/\beta\hbar$ is the harmonic constraint connecting the two most adjacent beads. For the ideal quantum problem, the full quantum Hamiltonian \hat{H} is established when $P \to \infty$. The introduction of this isomorphic relationship also means the quantum mechanical sampling can be mapped onto classical simulations by either Monte Carlo (MC)^{50,51} or MD⁵² methods. The potential of mean force with a collection of PIMD samples can thus be written as

$$F(\boldsymbol{\xi}_{PI}) = -\frac{1}{\beta} \ln \left\langle \frac{1}{P} \sum_{i=1}^{P} \delta(\boldsymbol{\xi}_{PI} - \boldsymbol{\xi}(\mathbf{x}_{i})) \right\rangle.$$
(3)

To accelerate computation, we incorporate of the PIMD and the reference-potential method (RPM) for the first time to calculate the statistical quantum mechanical properties at a level-of-interest Hamiltonian while simulating at a lower level Hamiltonian state. Additionally, we adopt the US method for enhancing the sampling. From K simulations, we can collect N_k configurations from the kth simulation. Each simulation is characterized by its specific potential function U_k , for $k \in 1 ..., K$. In the umbrella sampling method,

$$U_k(\mathbf{r}_n) = U_0(\mathbf{r}) + W_k(\boldsymbol{\eta}(\mathbf{r}))$$
(4)

where $U_0(\mathbf{r})$ is the unbiased Hamiltonian and $W_k(\mathbf{r})$ is the biasing potential acting on some chosen collective variables (CV) $\boldsymbol{\eta}(\mathbf{r})$. The unnormalized weight of each configuration under another Hamiltonian U_t is

$$\omega_t \left(\mathbf{r}_n \right) = \frac{e^{-\beta U_t(\mathbf{r}_n)}}{\sum\limits_{k=1}^K N_k e^{-\beta [U_k(\mathbf{r}_n) - f_k]}} = \frac{e^{-\beta \Delta U_t(\mathbf{r}_n)}}{\sum\limits_{k=1}^K N_k e^{-\beta [W_k(\boldsymbol{\eta}(\mathbf{r}_n)) - f_k]}},\tag{5}$$

in which f_k is the free energy of state k and is calculated by iteratively solving the Multistate Bennett Acceptance Ratio (MBAR)⁵³ equations

$$f_{i} = -\beta^{-1} \ln \sum_{n=1}^{N} \frac{e^{-\beta U_{i}(\mathbf{r}_{n})}}{\sum_{k=1}^{K} N_{k} e^{-\beta [U_{k}(\mathbf{r}_{n}) - f_{k}]}} \quad \forall i = 1, \dots, K.$$
(6)

Here, $N = \sum_{k=1}^{K} N_k$ is total number of snapshots collected in all the simulations, and $\Delta U_t(\mathbf{r}) = U_t(\mathbf{r}) - U_0(\mathbf{r})$. $\omega_t(\mathbf{r}_n)$ can be understood as the weighting factor for each configuration in a thermodynamic perturbation from the mixed reference potentials (U_k) to the target Hamiltonian (U_t) . Therefore, this method is referred to as the multistate thermodynamic perturbation (MsTP). Thermodynamic properties that depend only on atomic coordinates under U_t can thus be obtained as

$$\langle \hat{\mathbf{A}} \rangle_t = \frac{\sum\limits_{n=1}^N \omega_t \left(\mathbf{r}_n \right) \hat{\mathbf{A}} \left(\mathbf{r}_n \right)}{\sum\limits_{n=1}^N \omega_t \left(\mathbf{r}_n \right)}.$$
(7)

If **A** is an indication function δ of some chosen CV $\boldsymbol{\xi}(\mathbf{r})$

$$\delta(\boldsymbol{\xi}_m - \boldsymbol{\xi}(\mathbf{r})) = \begin{cases} 1, & \text{if } -\Delta \boldsymbol{\xi}/2 < \boldsymbol{\xi}_m - \boldsymbol{\xi}(\mathbf{r}) < \Delta \boldsymbol{\xi}/2 \\ 0, & \text{otherwise} \end{cases}, \tag{8}$$

the potential of mean force (PMF) under $U_t(\mathbf{r})$ can be written as

$$F_t(\boldsymbol{\xi}_m) = -\beta^{-1} \ln \sum_{n=1}^N \omega_t(\mathbf{r}_n) \delta(\boldsymbol{\xi}_m - \boldsymbol{\xi}(\mathbf{r}_n))$$
(9)

defined up to an additive constant. Similarly, the PMF under $U_0(\mathbf{r})$ can be written as

$$F_0(\boldsymbol{\xi}_m) = -\beta^{-1} \ln \sum_{n=1}^N \omega_0(\mathbf{r}_n) \delta(\boldsymbol{\xi}_m - \boldsymbol{\xi}(\mathbf{r}_n)), \qquad (10)$$

where

$$\omega_0(\mathbf{r}_n) = \frac{e^{-\beta U_0(\mathbf{r}_n)}}{\sum\limits_{k=1}^K N_k e^{-\beta [U_k(\mathbf{r}_n) - f_k]}} = \frac{1}{\sum\limits_{k=1}^K N_k e^{-\beta [W_k(\boldsymbol{\eta}(\mathbf{r}_n)) - f_k]}}$$
(11)

is the unnormalized weight for configuration \mathbf{r}_n under $U_0(\mathbf{r})$. To ameliorate the numerical instability originated from incomplete sampling, the weights $\omega_t(\mathbf{r}_n)$ under the target Hamiltonian are scaled by Gaussian-smoothing on the density-of-states.⁴⁷

In this work, we take U_0 as the PM6/MM⁵⁴ Hamiltonian, and U_t as the BLYP-D3/6-31G(d)/MM⁵⁵⁻⁵⁷ level of theory. For simplicity, they will be labeled as the SQM and DFT level of theories. Please also note that η is unnecessarily $\boldsymbol{\xi}$, but we set them equal in this work.

Simulations

One DMANH molecule, shown in Fig. 1,^{58,59} was solvated in a TIP3P water⁶⁰ sphere with a radius of 25 Å using the LEaP module in the AmberTools19 package.⁶¹ One chlorine ion was added for neutralization. The QM region contained only the DMANH molecule, and the MM region comprised all the solvent molecules and the counter ion. In the MM region, the SHAKE algorithm⁶² was applied to constrain all the bonds involving hydrogen atoms. The system was energy-minimized for 2000 steps and then heated up to 298 K in 100 ps. Finally, a 100-ps classical MD simulation was conducted for further relaxation of the system. Temperature was regulated using the Langevin thermostat with a collision frequency of 2.0 ps^{-1} .⁶³

The CV was defined as the difference in the N–H bond lengths, i.e. $d_{N_{a}H} - d_{N_{d}H}$, where $d_{N_{a}H}$ is the distance between the proton $\stackrel{\oplus}{H}$ and the acceptor nitrogen atom N_a, and $d_{N_{d}H}$



Figure 1: Molecular structure of DMANH

the distance between the proton $\overset{\text{w}}{\text{H}}$ and the donor nitrogen atom N_d. The CV, ranged from -0.15 Å to 1.10 Å, was discretized into 26 windows in total. Harmonic potentials $W_k(\mathbf{x}) = \frac{1}{2}k_{\boldsymbol{\xi}}(\boldsymbol{\xi} - \boldsymbol{\xi}_k)^2$ were used with $k_{\boldsymbol{\xi}} = 100 \text{ kcal} \cdot \text{mol}^{-1} \cdot \text{Å}^{-2}$ for all the windows. We first performed the primitive approximation PIMD (PRIMPIMD)⁵⁰ with 16 beads for each QM atom for 1-ns per window, and then an additional 1-ns simulation was performed for each of the first 16 windows (with RC between -0.15 Å and 0.60 Å) to improve the convergence in this region. The temperature was regulated using the "middle scheme" Langevin thermostat.^{64,65} The step size was set to 0.5 fs. Configurations were saved every 1000 steps (500 fs) for single point energy calculations at the DFT level, as well as the SQM level. Due to the symmetry of the molecule, we only calculated the PMF along the CV with positive values. The potential of mean force at the SQM level was generated via the MBAR analysis, and that at the DFT level was calculated with the MsTP and was smoothed using the Gaussian process regression.⁶⁶

Results and Discussion

Reweighting entropy (RE), is a measure of the reliability of the RPM. We have previously shown that when RE is greater than 0.3 in the MsTP calculations, the extrapolation process is reliable.⁴⁵ When it is below 0.3, large biases may reside in the free energy profile. As shown

in Fig. 2, the free energy profile under the DFT level is reliable when the CV is smaller than 0.8 Å. When the CV is greater than 0.8 Å, RE plunges. This is the consequence of the large difference in the preferred structures under these two Hamiltonians, i.e. SQM and DFT. Shown in Fig. 3 are the means and fluctuations of the local structures for the proton transfer reaction. With the CV increases from 0.00 Å to 0.80 Å, $d_{N_{dH}}$ decreases from around 1.34 Å to about 1.05 Å, and $d_{N_{aH}}$ increases from 1.34 Å to 1.85 Å. These distance variations are very similar to those under the SQM Hamiltonian as shown in Fig. S1. However, $d_{N_{dH}}$ shows a sudden drop when the CV is greater than 0.8 Å, and deviates from the mean bond length under the SQM Hamiltonian, indicating an insufficient overlap in the sub-phase space under these two Hamiltonians. The difference is more obvious for the N_d-H-N_a angle. Therefore, thermodynamic properties with CV greater than 0.8 Å have not reached convergence, and more samples are required in this region. For the PMF analysis at the DFT level in the following, we can only trust the results for the region with CV below 0.8 Å.



Figure 2: Reweighting entropy

The free energy profiles under the SQM and DFT levels are shown in Fig. 4. Under the SQM level, the uncertainties are much smaller than their counterparts under the extrapolated DFT level. The large magnitude in the uncertainties under the DFT level is the consequence



Figure 3: Structural alternations during the proton transfer process at the DFT/MM level from MsTP. (A) Distance between the proton (H) and the N_d atom. (B) Distance between the proton (H) and the N_a . (C) Distance between the N_d and the N_a atoms. (D) Angle of N_d -H-N_a. The shaded areas are the standard error.

of the sampling inefficiency when the MBAR weights are assigned to the samples. As shown in Eq. 5, the weight decays exponentially as the energy difference between the two Hamiltonians increases. Precisely, ΔU_t is the difference in the deviations of the potential energies from their respective means, since the difference in the means can be canceled in normalization. Under the SQM level, the minimum in the free energy profile locates at $\text{CV} \approx 0.6 \text{ Å}$, which is about 0.1 Å larger than the minimum under the DFT level. This indicates that in the optimal structure under the SQM level, the proton prefers to be closer to one of the nitrogen atoms, while under the DFT level the proton is more diffusive. This can be explained by the difference in the basis sets used in the SQM and DFT calculations. PM6 used the minimum basis set, while a larger basis set 6-31G(d) was used in the DFT calculations. Both of the profiles show a reaction free energy barrier of about 1.2 kcal/mol. This picture is different from the results in a recent study by Zhou and Wang, in which the reaction is barrierless.⁶⁷ The disagreement comes from the difference in the Hamiltonians. In their studies, all the atoms were quantum particles, while in the current study only the DMANH molecule was treated quantum mechanically. Quantum-mechanically described water molecules can stabilize the delocalized proton, and thereby lowers the reaction barrier. In the current work, we are not aiming at reproducing the results of a full-QM PIMD model. However, the central idea developed in the current work can be applied to a full-QM PIMD model, if a proper reference Hamiltonian can be found. This is beyond the interest of the current work. For the CV to the right side of the minimum, the potential of mean force increases very fast w.r.t the CV under the DFT level than under the SQM level, which indicates a higher probability of a shared proton between the nitrogen atoms under the DFT level.

The estimated CPU times of obtaining PMF at the BLYP-D3 level with direct QM/MM and RPM are shown in Table 1. The CPU time of the RPM includes two parts, i.e. the CPU time for collecting the trajectories at the PM6/MM level and the CPU time for the single point energy calculations at both the PM6/MM and BYLP-D3/MM level. While the direct QM/MM method at the BLYP-D3/MM level only requires the time for the simulations.



Figure 4: Free energy profiles of the proton transfer under different levels of theory

Since the PM6/MM level is several orders of magnitude more efficient than BLYP-D3/MM level and the configurations were saved once every 1000 steps of MD propagation for the single point energy calculations at the DFT level of theory, a 545-fold enhancement in the efficiency was observed for the RPM method as compared to a direct PIMD simulations at the same level of theory.

Table 1: Estimated CPU Time in a unit	of Days. Assuming one node with 28
cores of Intel Xeon Gold 6132 CPU 2.60	GHz was used.

RP method		Direct DFT a	
Sampling	Energy Evaluation	Total	DHELU DI I
1.04 K	1.25 K	2.29 K	1250 K

^a Estimated CPU time assuming the number of windows and simulation length for each window

Conclusion

The calculations of thermodynamic properties from computer simulations require independent and identically distributed samples. The long correlation time of chemical processes in condensed phases plagues the simulations with slow convergence in thermodynamic properties and poses a challenge for the computational studies at ab initio levels of theory. This difficulty is more severe for PIMD, in which the representation of quantum effect in singleparticle systems is transformed into a classical problem of discrete cyclic model systems with a number of beads for each atom. The reference-potential methods can be a remedy for ameliorating the large expense by leveraging an inexpensive sampling method and a postprocessing process on the harvested samples. In this work, the proton transfer within a protonated 1,8-bis(dimethylamino)naphthalene molecule was studied, and the free energy profile at the BLYP-D3/6-31G(d)/MM level of theory was calculated using a more efficient sampling at the PM6/MM level. With a finite number of samples, the reliability of this reference-potential method heavily depends on the overlap in the phase space between the target (BLYP-D3/6-31G(d)/MM) Hamiltonian and the reference (PM6/MM) Hamiltonian. The results show that when the CV, which is defined as the difference in the distances from the proton to the acceptor and to the donor, is below 0.8 Å, the potential of mean force and the structural properties can be reliably produced with a 545-fold enhancement in the efficiency.

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Supporting Information Affordable *Ab Initio* Path Integral for Thermodynamic Properties via Molecular Dynamics Simulations Using Semiempirical Reference Potential

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Figure S1: Structural alternations during the reaction at the PM6/MM level. A) Distance between the transferred proton (H) and the donor nitrogen (N_d) atom. B) Distance between the transferred proton (H) and the acceptor nitrogen atom (N_a) . C) Distance between the donor (N_d) and the acceptor nitrogen (N_a) atoms. D) Angle of N_d -H-N_a.



Figure S2: Free energy profiles with Gaussian process regression at the BLYP-D3 level using 200 snapshots, 1000 snapshots and 2000 snapshots from each window simulation.



Figure S3: Distribution of ΔU