

Solving Nonlinear Eigenvalue Problems in Electronic Structure Calculations

Chao Yang Juan Meza Lin-wang Wang
Computational Research Division
Lawrence Berkeley National Lab

Quantum Many-Body Problems



$$H\psi_i(r_1, r_2, \dots, r_N) = E_i\psi_i(r_1, r_2, \dots, r_N)$$

$$H = -\frac{\hbar}{2m} \sum_{i=1}^N \nabla_i^2 + \sum_{i=1}^N v(r_i) + \frac{1}{2} \sum_{i \neq j} \frac{e^2}{|r_i - r_j|}$$

- ψ contains all the information of the system;
- $|\psi_i|^2$ probability density of finding electrons at a certain state i .
- E_i quantized energy of the system.
- 3N-coordinate space
- Manageable N
 - < 3 for analytic calculations (e.g. H, He, etc.)
 - O(10) for configuration interaction simulations
 - O(100) for quantum Monte Carlo simulations
- $N \leq 100$ for an atom or crystal;
for nano-structures $\sim (10^3 - 10^6)$

Reducing many-body problem to a (nonlinear) single-particle problem (Density Functional Theory)



The ground state density of an atomistic system can be found by minimizing a total energy functional with respect to single particle wave functions (Hohenberg, Kohn, Sham)

$$E_{total}(X) = E_{kinetic} + E_{ionic} + E_{Hartree} + E_{xc}$$

$$E_{kinetic} = \frac{1}{2} \text{trace}(X^T L X)$$

$$E_{ionic} = \frac{1}{2} \left[\text{trace}(X D_{ion} X^T) + \sum_i \sum_\ell (x_i^T w_\ell)^2 \right]$$

$$E_{Hartree} = \frac{1}{4} \rho(X)^T S \rho(X)$$

$$E_{xc} = e^T (f_{xc} [\rho(X)])$$

- single particle wave functions

$$X = (x_1, x_2, \dots, x_k), x_i \in \mathbf{R}^n$$

- n – real space grid size, e.g. $32^3 \sim 32000$
- k – number of occupied states, 1-10% of n
- Charge density

$$\rho(X) = \text{diag}(X X^T)$$

- **Solve**
$$\min_X E_{total}(X)$$
$$\text{s.t. } X^T X = I$$

- **First order necessary (KKT) condition**

$$\nabla_X \mathbf{L}(X) = 0,$$
$$X^T X = I,$$

where $\mathbf{L}(X) = E_{total}(X) - \text{trace}(\Lambda^T (X^T X - I_k))$.

Nonlinear Eigenvalue Problem



- **KKT condition (Kohn-Sham equation)**

$$\left[\underbrace{L + D_{ion} + \sum_{\ell} w_{\ell} w_{\ell}^T + \text{Diag}(S\rho(X)) + \text{Diag}(g_{xc}(\rho(X)))}_{H(X)} \right] X = X\Lambda$$

$$X^T X = I$$

- **The solution is not unique (look for an invariant subspace)**

$$\rho(X) = \rho(XQ), \text{ for any } Q \text{ such that } Q^T Q = I_k$$

The Self Consistent Field Iteration



- **Input: initial guess X_0 and L, D_{ion}, S, w_ℓ**
- **Output: $X = \arg \min(E_{total}(X))$
s.t. $X^T X = I_k$**
- **Major steps**
 - **For $i=1,2,\dots$, until converged $H(X^{(i)})X^{(i)} \approx X^{(i)}\Lambda^{(i)}$**
 - 1) **Form $H^{(i)} = H(X^{(i)})$**
 - 2) **Compute k smallest eigpairs of $H^{(i)}$**
$$X^{(i+1)} = \arg \min [\text{trace}(X^T H^{(i)} X)]$$
s.t. $X^T X = I_k$

SCF Iteration



- **Most widely used**
- **Does not always converge**
 - The objective $E_{total}(X^{(i)})$ does not always decrease
- **Little convergence theory**
 - Fixed point iteration?
$$X^{(i+1)} = F(X^{(i)}), \text{ but what is } F(\cdot)?$$
- **Must solve a large-scale eigenvalue problem at each iteration**
 - Dense eigensolver (very expensive)
 - Iterative solver: preconditioned conjugate gradient (accuracy, stopping criterion)

Optimization Point of View



SCF minimizes a sequence of surrogate models

- **True objective**

- $E_{kinetic} = \frac{1}{2} \text{trace}(X^T LX)$

- $E_{ionic} = \frac{1}{2} \left[\text{trace}(XD_{ion}X^T) + \sum_i \sum_\ell (x_i^T w_\ell)^2 \right]$

- $E_{Hartree} = \frac{1}{4} \rho(X)^T S \rho(X)$

- $E_{xc} = e^T (f_{xc}[\rho(X)])$

- **Surrogate model**

- $E_{surrogate} = \frac{1}{2} \text{trace}(X^T H(X^{(i)})X)$

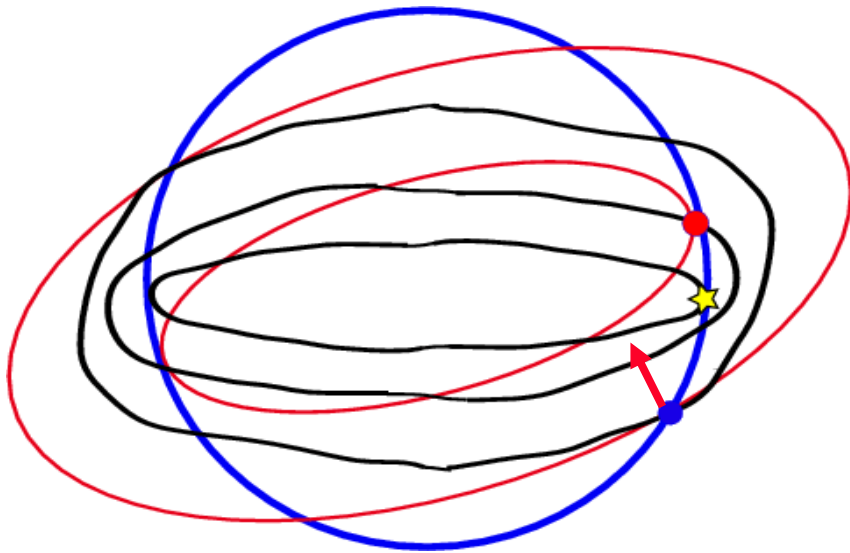
- $$\begin{aligned} H(X) &= L + D_{ion} + \sum_\ell w_\ell w_\ell^T \\ &+ \text{Diag}(S\rho(X)) \\ &+ \text{Diag}(g_{xc}(\rho(X))) \end{aligned}$$

- **Gradient:** $\nabla_X E_{total} = H(X)X$

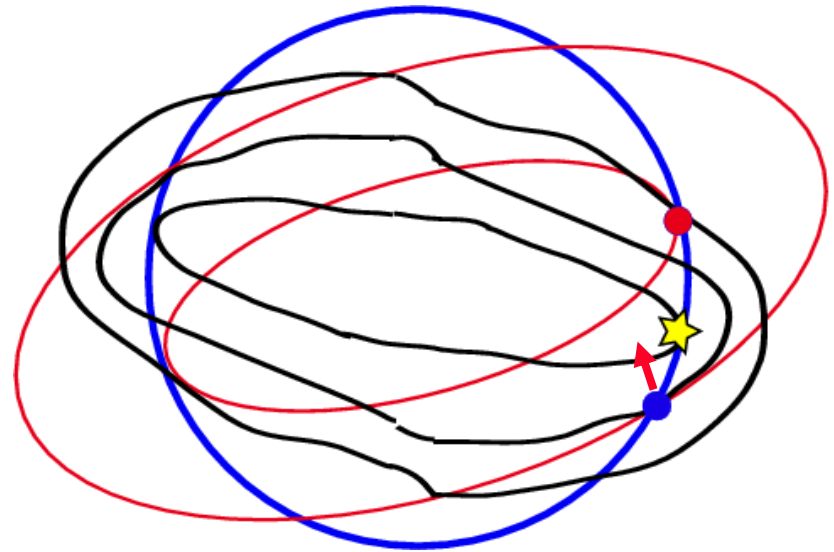
- **Gradient:** $\nabla_X E_{surrogate} = H(X^{(i)})X$

$$\nabla_X E_{total}(X^{(i)}) = \nabla_X E_{surrogate}(X^{(i)})$$

Geometry



SCF works



SCF fails

Improving SCF



- **Better Surrogate Model?**
 - Can't afford to use local quadratic approximation (Hessian too expensive)
 - Charge mixing or DIIS (H is a function of the charge density)
$$\rho^{(i+1)} = \rho^{(i)} + \gamma(\rho(X^{(i+1)}) - \rho^{(i)})$$
- **Use Trust Region?**
 - TRSCF by Thogersen, Olsen, Yeager & Jorgensen (2004)
 - Globally convergent trust-region by Francisco, J. Martinez & L. Martinez (2004)

Direct Minimization



- **Minimize the total energy directly**
- **Maintain the orthonormality constraint**
- **Search direction**
 - **Gradient, conjugate gradient based approach**
 - **Brendt & Zunger (1982)**
 - **Gillan (1989)**
 - **Payne, Teter, Allen, Arias & Jaoannopoulos (1992)**
 - **Kresse & Furthmuller (1996)**
 - **Quasi-Newton**
 - **Edelman, Arias & Smith (1998)**
 - **Voorhis & Head-Gordon (2002)**
- **Line search**
 - **Re-parametrize** $x^{(i+1)} = x^{(i)} \cos \theta + p^{(i)} \sin \theta$
 - **Move along geodesic**

New Approach



- **Conjugate Gradient-like scheme (no Hessian approximation)**
- **Block (“all band”) method**
- **Determine search direction and “step length” simultaneously**

$$X^{(i+1)} = X^{(i)}G_x^{(i)} + \underbrace{P^{(i-1)}G_p^{(i)} + R^{(i)}G_r^{(i)}}_{\text{search direction } P^{(i)}}$$

$$R^{(i)} \equiv \nabla_X \mathbf{L} = H^{(i)} X^{(i)} - X^{(i)} \Theta^{(i)},$$
$$\Theta^{(i)} = \text{diag}(X^{(i)T} H^{(i)} X^{(i)})$$

Choose $G_x^{(i)}$, $G_p^{(i)}$, and $G_r^{(i)}$ ("step length") to :

1. $\min E_{total}(X^{(i+1)})$
2. maintain $X^{(i+1)T} X^{(i+1)} = I_k$

Yang, Meza & Wang, LBNL Tech Report-57434, 2005

Minimization within a Subspace



- **Let** $Y = (X^{(i)}, R^{(i)}, P^{(i-1)})$

- **Solve**

$$\min_G E_{total}(YG)$$

$$\text{s.t. } G^T Y^T YG = I_k$$

- **Equivalent to solving**

$$\hat{H}(G)G = BG\Omega_k,$$

$$G^T BG = I_k,$$

where

$$\hat{H}(G) = Y^T \left(L + D_{ion} + \sum_{\ell} w_{\ell} w_{\ell}^T + \text{Diag}(S\rho(YG)) + \text{Diag}(g_{xc}(\rho(YG))) \right) Y,$$

$$B = Y^T Y$$

DCM Algorithm



For $i=1,2,\dots$ until convergence

1. Form $H^{(i)} = H(X^{(i)})$
2. Compute $R^{(i)} = K^{-1}(H^{(i)} X^{(i)} - X^{(i)} \Theta^{(i)})$,
where $\Theta^{(i)} = \text{Diag}(X^{(i)T} H^{(i)} X^{(i)})$, K is a preconditioner
3. If ($i>1$) then
 - set $Y \leftarrow (X^{(i)}, R^{(i)}, P^{(i-1)})$
4. else
 - set $Y \leftarrow (X^{(i)}, R^{(i)})$
5. Solve $\min_{G^T Y^T Y G = I_k} E_{total}(Y^{(i)} G)$
6. Set $X^{(i+1)} = YG$
7. If ($i>1$) then
 - set $P^{(i)} \leftarrow Y^{(i)}(:, k+1:3k)G(k+1:3k,:)$
8. else
 - set $P^{(i)} \leftarrow Y^{(i)}(:, k+1:2k)G(k+1:2k,:)$

Solving the projected problem



- **Use SCF**
 - No guarantee of convergence
 - But full convergence may not be necessary, all we need is sufficient decrease in $E_{total}(YG)$
- **Constrained Quasi-Newton**
 - May be feasible due to the much smaller size of the problem
 - Optimization on Grassman manifold (Edelman et al 1998, Van Vooris & Head-Gordon 2002)

Estimated Computational Complexity



(in terms of the number of MATVECs $y \leftarrow H^{(i)}x$)

DCM

- **Outer iteration:**
 - **Gradient calculation**
- **Inner iteration**
 - **Update the Hamiltonian**

k MATVECs/iter

$$Y^T [\text{Diag}(R\rho(YG)) + \text{Diag}(g(\rho(YG)))]Y$$

- **Overall:**
 $k+p$ MATVECs/outer iter

SCF

- **Outer iteration:**
 - **Update the Hamiltonian**
- **Inner iteration:**
 - **Gradient calculation**

$$\text{Diag}(R\rho(X^{(i)})) + \text{Diag}(g_{xc}(\rho(X^{(i)})))$$

k MATVECs/iter

- **Overall:**
 $k*p$ MATVECs/outer iter

Assumption: k is much smaller than n

Numerical Example

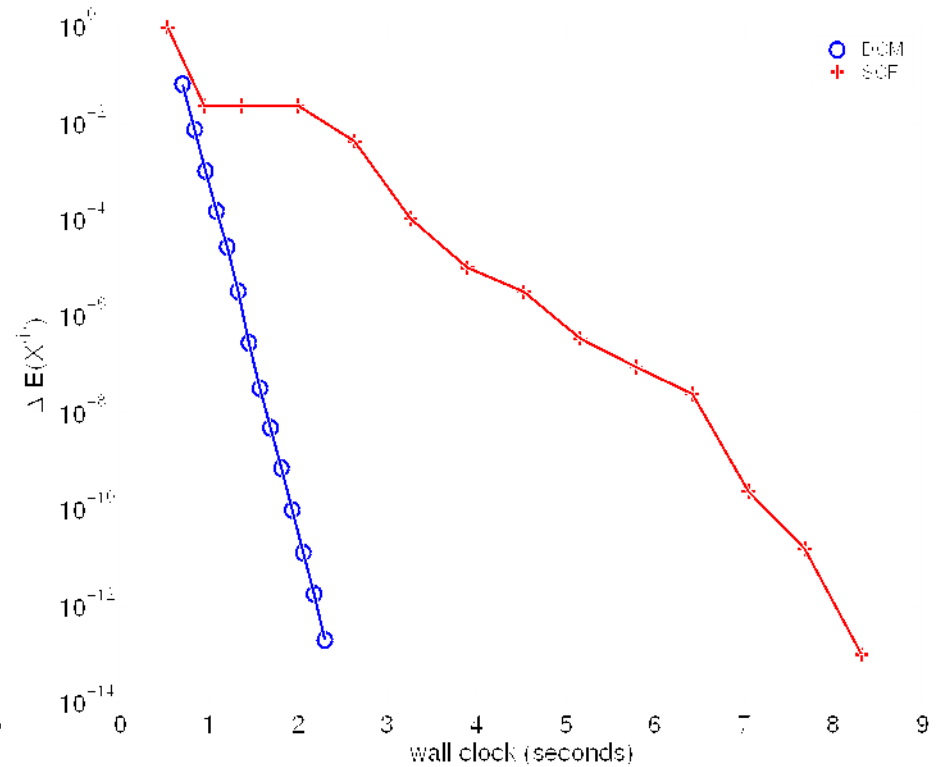
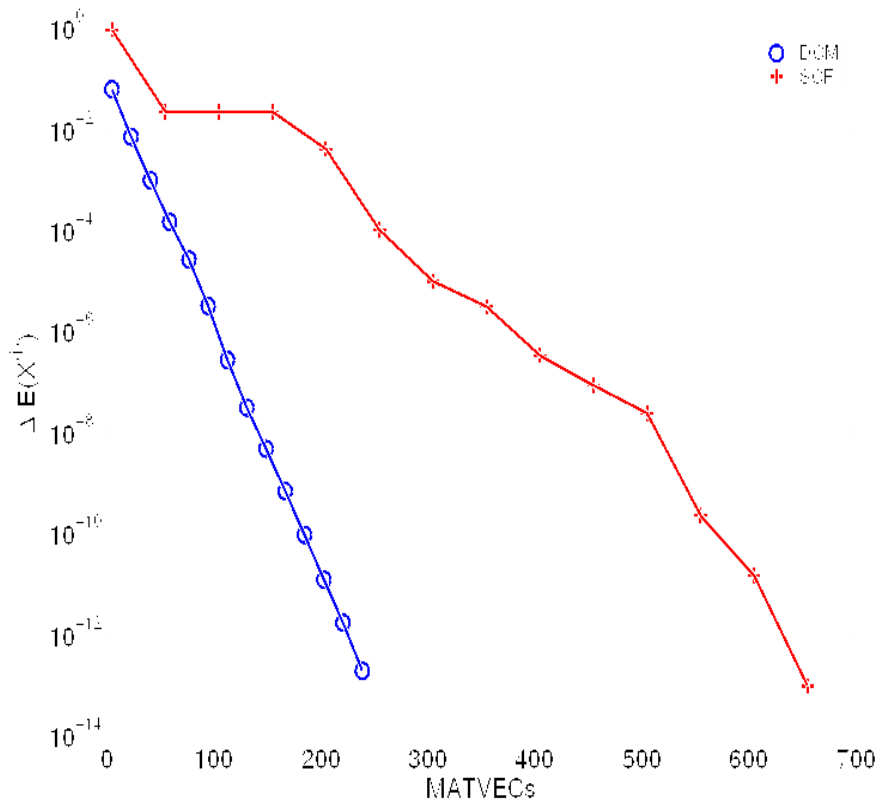


- **Atomistic system: SiH₄**
- **Discretization: spectral method with plane wave basis: $n=32^3$ in real space, $N=2103$ (# of basis functions) in frequency space**
- **Number of occupied states: $k = 4$**
- **PETOT version of SCF uses 10 PCG steps (inner iterations) per outer iteration**
- **DCM: 3 inner iterations**
- **Compare the change of the objective function with respect to the number of MATVECs performed & timing**
- **Parallelized using MPI on 16 IBM Power3 CPUS**

Performance



$$\Delta E(X^{(i)}) = E_{total}(X^{(i)}) - E_{min}$$



Conclusion



- **Nonlinear eigenvalue problem in electronic structure calculation should be solved as an optimization problem**
- **No need to solve linear eigenvalue problems to full accuracy in SCF**
- **SCF can be further improved (better surrogate model, trust region)**
- **DCM competitive with SCF (Reduced a large-scale nonlinear minimization problem to a sequence of much smaller problems)**
- **Further research required to solve the small nonlinear problem efficiently**