# Quantum Element Method for Multi-Dimensional Nanostructures Enabled by a Projection-based Learning Algorithm

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## NANOSTRUCTURES

□ Useful applications in medicine, chemistry and material science

□ Often with nanostructures one needs to work with the Schrödinger equation

$$\nabla \cdot \frac{-\hbar^2}{2m^*(\vec{r})} \nabla \psi(\vec{r}) + U(\vec{r})\psi(\vec{r}) = E\psi(\vec{r})$$

- □ Large-scale multi-dimensional simulations of the Schrödinger equation often require immense computational power and time when using direct numeric simulations (DNS)
  - □ Like many other special dependent simulations, a large number of DoF are needed, especially in regions where high resolution is needed

## ESSENTIALS OF COMPACT MODELING

- Employ projection or Mathematical Transformation to reduce the DoF
  - Commonly used projections:
    - **D** Fourier Series:  $f(x) = \sum_{-\infty}^{\infty} a_n e^{jnkx}$ : Periodic Harmonic Expansion
    - □ Legendre Polynomials:  $f(x) = \sum_{\ell=0}^{n} a_{\ell} P_{\ell}(x)$ : Spherical Harmonic Expansion
    - **D** Bessel Functions:  $f(x) = \sum_{n=0}^{M} a_n J_{n(x)}$ : Cylindric Harmonic Expansion
  - □ Instead of assuming a basis, a learning algorithm can extract the modes:
  - Examples:
    - **PCA**: Principal component analysis
    - SVD: Singular value decomposition



https://www.theochem.ru.nl/~pwormer/Kno wino/knowino.org/wiki/Spherical\_harmonics .html

### PROPER ORTHOGONAL DECOMPOSITION OF THE SCHRÖDINGER EQN.

□ To reduce DoF of the Schrödinger equation one will project it onto modes found via POD

$$\psi(\vec{r}) = \sum_{i=1}^{M} a_i \eta_i(\vec{r})$$

**D** POD modes  $\eta(\vec{r})$  are found such that it maximizes its mean square inner product with the solution

$$\left\langle \left( \int_{\Omega} \psi(\vec{r}) \, \eta(\vec{r}) d\Omega \right)^2 \right\rangle / \int_{\Omega} \eta(\vec{r})^2 \, d\Omega$$

□ Employing Calculus of variations techniques, the maximization process results in an eigenvalue problem of the 2-point correlation matrix of the data

$$\int_{\Omega'} \langle \psi(\vec{r}) \otimes \psi(\vec{r'}) \rangle \eta(\vec{r'}) d\Omega' = \lambda \eta(\vec{r})$$

□ Solved modes minimize the least square error with the smallest number of basis functions

#### QUANTUM POD METHODOLOGY FOR SINGLE ELEMENT

- Data collected via applying electric fields or external potentials to underlining nanostructure
- For each sample (applied electric field) the Schrödinger Eqn. is solved using DNS
- □ WFs of the first few N QS are collected for  $N_s$  electric fields  $\Psi_i$ : Set of WF data for Electric field *i*



# SINGLE ELEMENT PROJECTION ONTO POD MODES

Schrodinger equation formed via a linear combination of POD Modes:

$$\psi(\vec{r}) = \sum_{i=1}^{M} a_i \eta_i(\vec{r})$$

Galerkin Projection of the Schrodinger equation onto the ith POD mode:

$$\int_{\Omega} \nabla \eta_i \cdot \frac{\hbar^2}{2m^*} \nabla \psi d\Omega + \int_{\Omega} \eta_i U \psi d\Omega - \int_{S} \eta_i \frac{\hbar^2}{2m^*} \nabla \psi \cdot d\vec{S} = E \int_{\Omega} \eta_i \psi d\Omega$$

Unlike PCA/SVD, the POD simulation methodology involves a second projection incorporating the governing equation into the model

Forms Hamiltonian Equation in POD Space:  $H_{\eta}\vec{a} = (T_{\eta} + B_{\eta} + U_{\eta})\vec{a} = E\vec{a}$ 

$$\boldsymbol{T}_{\eta i,j} = \int_{\Omega} \left[ \nabla \eta_i(\vec{r}) \cdot \frac{\hbar^2}{2m^*} \nabla \eta_j(\vec{r}) \right] d\Omega \qquad \boldsymbol{B}_{\eta i,j} = -\int_{S} \eta_i(\vec{r}) \frac{\hbar^2}{2m^*} \nabla \eta_j(\vec{r}) dS \qquad \boldsymbol{U}_{\eta i,j} = \int_{\Omega} \eta_i(\vec{r}) U(\vec{r}) \eta_j(\vec{r}) d\Omega$$

Interior kinetic energy matrix Boundary kinetic energy matrix Potential energy matrix 6

#### **Train Elements**

# QUANTUM ELEMENT METHOD (QEM)<sub>Training Structures</sub>

- To form the POD modes, DNS data is required
  - Large structures might make gathering this training data prohibitive due to large simulation times.

□Solution: OEM

Incorporate domain decomposition in which trained elements can be stitched using the Discontinuous Galerkin Method

Aligning with the engineering paradigm of building Blocks the QEM offers a cost-effective approach to simulating large nanostructures



SCHRODINGER EQUATION, IN POD SPACE (QEM)

$$\int_{\Omega} \nabla \eta_i \cdot \frac{\hbar^2}{2m^*} \nabla \psi d\Omega + \int_{\Omega} \eta_i U \psi d\Omega - \int_{S} \eta_i \frac{\hbar^2}{2m^*} \nabla \psi \cdot d\vec{S} = E \int_{\Omega} \eta_i \psi d\Omega$$

Applying the Discontinuous Galerkin method to the Schrodinger equation in POD space the results in:

$$\sum_{j=1}^{M_p} \left( T_{\eta_p,ij} + U_{\eta_p,ij} \right) a_{p,j} + \sum_{q=1,q\neq p}^{Nel} \sum_{j=1}^{M_p} B_{p,pq,ij} a_{p,j} + \sum_{q=1,q\neq p}^{Nel} \sum_{j=1}^{M_p} B_{pq,ij} a_{p,j} = E a_{p,i}$$

Interior Kinetic Interior Potential energy Matrix energy Matrix

 $\mu$  penalty parameter allowing control preference between continuity of flux vs value

$$B_{p,pq,ij} = -\frac{1}{2} \int_{\Omega_p} \frac{\hbar^2}{2m_p^*} \left[ (\nabla \eta_{p,i}) \eta_{p,j} + \eta_{p,i} (\nabla \eta_{p,j}) \right] \cdot d\vec{S} + \mu \int_{S_{pq}} \frac{\hbar^2}{2m_p^*} \eta_{p,i} \eta_{p,j} dS$$
$$B_{pq,ij} = \frac{1}{2} \int_{\Omega_p} \frac{\hbar^2}{2m_p^*} \left[ (\nabla \eta_{p,i}) \eta_{q,j} + \eta_{p,i} (\nabla \eta_{q,j}) \right] \cdot d\vec{S} - \mu \int_{S_{pq}} \frac{\hbar^2}{2m_p^*} \eta_{p,i} \eta_{q,j} dS$$

Diagonal Boundary Kinetic Energy Matrix Off-Diagonal Boundary Kinetic Energy Matrix

#### TRAINING AND MODE GENERATION

Two 9-element training structures of quantum dots composed of the GaAs/InAs heterostructure are for training

- □ 5 electric field applied in each of the two orthogonal directions ranging from -0.35kv/cm and +0.35kv/cm are applied to these structures.
- □ For each Electric Field, the WFs of the first 6 QSs are collected.

☐ After Training the POD modes, the Method of Snapshots is applied to each element generating a unique set of Modes for each.



### Training Elements 1and 2





Vertical Training Elements		
Horizontal Training Elements	<b>.</b>	



#### TRAINING ELEMENT 3 AND 4



Elements

#### TEST STRUCTURE

100 E3

90

80 70

60 50 k

40

0

0

20

40

60

x (nm)

80

- □ The POD methodology is applied to the training structure on right.
- □ Unlike during training, a twocomponent electric field is applied  $\downarrow kV$  kV

$$\vec{E} = 25 \frac{kV}{cm}\hat{x} - 15 \frac{kV}{cm}\hat{y}$$

**Training Nanostructure** 

E2 E1

20

40

80

60

x (nm)

100

100 0

E3



#### Test Nanostructure



# ADEQUACY OF TRAINING RELATIVE TO TEST STRUCTURE



X

#### ADEQUACY OF TRAINING RELATIVE TO TEST STRUCTURE CONT. Training Elements Test



X

X

# $\psi$ Results

 Alignment with POD and DNS solution after around 10 modes per Element



## LS ERROR PLOT AND ENERGY ERROR

#### Tab. 1. Percentage Error of Eigenenergy in Each State

QS	POD Energy (eV)	DSN Energy (eV)	(%) Difference
1	0.29888	0.29701	0.62631
2	0.30360	0.30229	0.43295
3	0.34313	0.34119	0.56768
4	0.34545	0.34354	0.55297
5	0.35336	0.35097	0.67970
6	0.38199	0.37969	0.60448
7	0.38521	0.38263	0.67287
8	0.39698	0.39371	0.82581

- DNS uses 90601 DoF State: 5 State: 6 State: 10 LS Error (%)  $10^{\circ}$ State: State: State: 10-1 State: 15 20 25 5 10 Number of Modes per Element □ LS error for trained states is around 1% or less after including 10 modes for trained states.
  - States 7 and 8 which are not trained reach an errors or around 3% and 4% respectively after including 20 Modes per element.
- Energy Percent difference between DNS and POD is less than 0.7% for trained states and 0.83% for untrained states

#### CONCLUSION

- QEM can greatly reduce the DoF of the problem
  90601 to around 40 DoF
- QEM confirms the engineering paradigm of building blocks
  Offers promising value within engineering design
- □ In general, higher QSs require more POD modes to reach sufficient accuracy
- The QEM can stitch together blocks with incomplete training
- Training with single orthogonal component electric fields allows simulation of nanostructures subjected to two components
- □ Higher untrained QSs can be reasonably predicted via the QEM
- **G** For large Nanostructures, the POD Hamiltonian matrix becomes sparse