

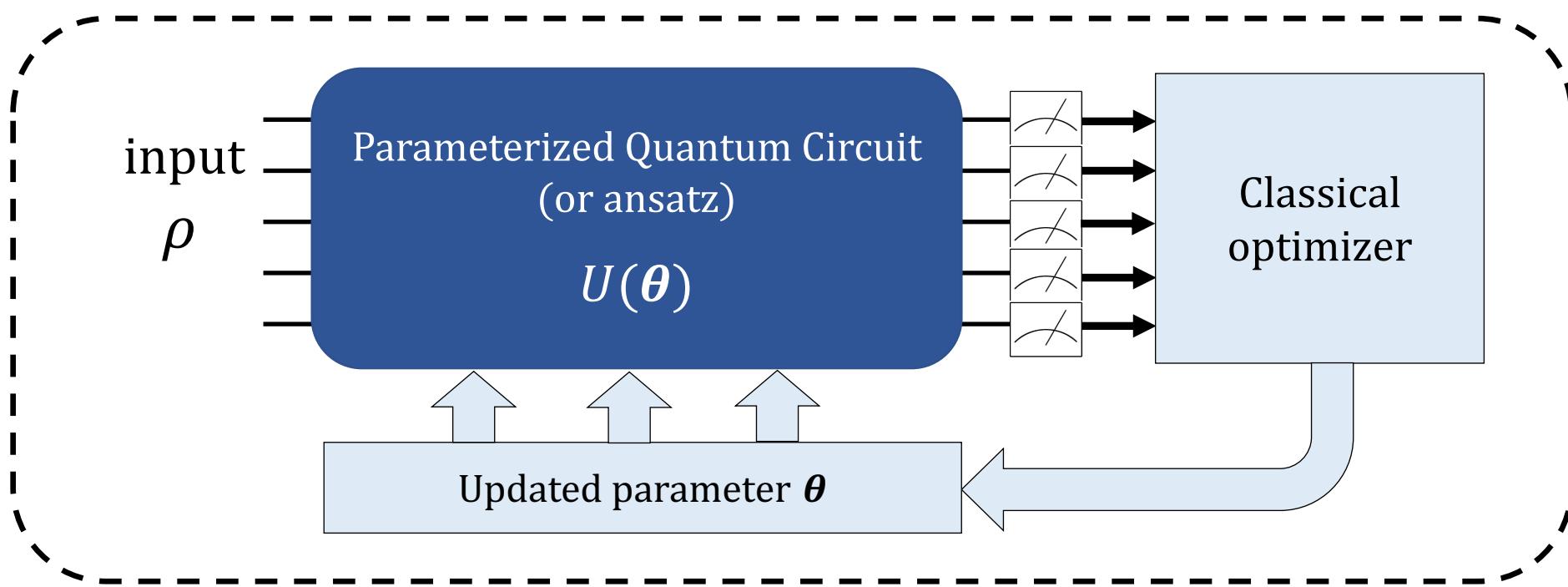
Suffix averaging technique for improving optimization result in VQAs

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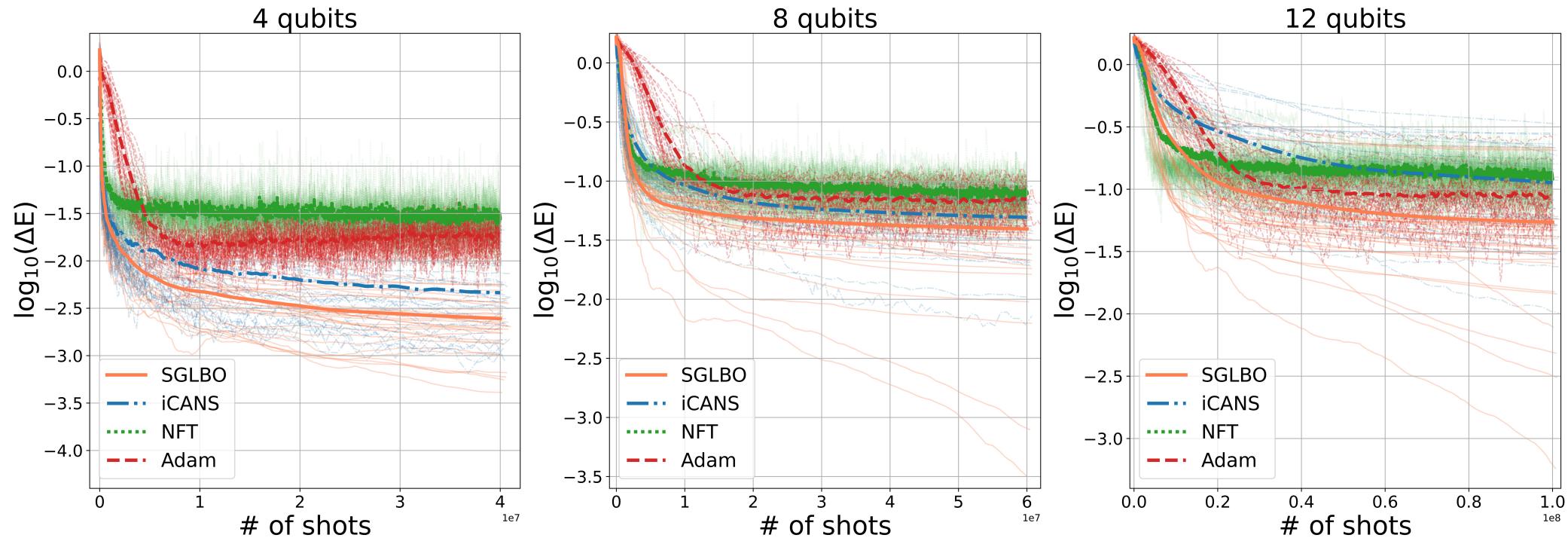
Optimization in VQAs



Task: $\theta^* = \operatorname{argmin}_\theta f(\theta)$

Stochastic gradient line Bayesian optimization (SGLBO)

S. Tamiya and H. Yamasaki, npj Quant. Info. **8**:90 (2022)



Results

- Propose SGLBO by combining SGD for estimating gradients and BO for estimating optimal step size.
- Introduce two noise-reduction techniques, adaptive shot strategy and **suffix averaging**.
- SGLBO exhibits high accuracy and high noise resilience compared to state-of-the-art optimizers.

Suffix averaging (SA)

- In VQAs, we usually utilize the point $\hat{\theta}^{(T)}$ obtained by final iterate as a result of an optimization .
- However, the points $\{\hat{\theta}^{(t)}\}_t$ may oscillate around a local minimum due to statistical effects.

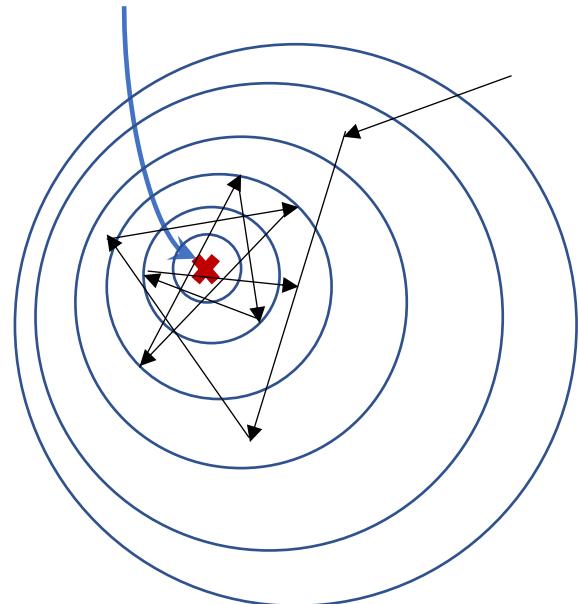
Iteration	1	2	$T - 2$	$T - 1$	T
Point	$\hat{\theta}^{(1)}$	$\hat{\theta}^{(2)}$	$\hat{\theta}^{(T-2)}$	$\hat{\theta}^{(T-1)}$	$\hat{\theta}^{(T)}$

$\underbrace{\hspace{10em}}$

N_{SA} points
take average

$$\hat{\theta}^* \leftarrow \frac{1}{N_{SA}} \sum_{i=1}^{N_{SA}} \hat{\theta}^{(T-i+1)}$$

Local minimum θ^*



Suffix averaging (SA)

```
[5] optimizer = ADAM(maxiter=1000)
    ansatz = TwoLocal(2, ['ry'], 'cx', "linear")
    grad = Gradient(grad_method="param_shift")
```

✓ 0.1s

Python

```
[6] suffix_optimizer = SuffixAveragingOptimizer(optimizer, n_params_suffix=50)
```

✓ 0.2s

Python

```
[7] counts = []
    values = []
    def store_intermediate_result(eval_count, parameters, mean, std):
        counts.append(eval_count)
        values.append(mean)
    vqe = VQE(ansatz, suffix_optimizer, callback = store_intermediate_result, gradient = grad, quantum_instance=quantum_instance)
```

✓ 0.2s

Python

```
[8] result = vqe.compute_minimum_eigenvalue(operator=h2_op)
```

✓

Python

```
[18] print("Final point:", values[-2])
    print("Suffix averaged point:", result.optimal_value)
    print("Improvement:", values[-2]-result.optimal_value)
    print("Optimal:", -1.85727503)
```

✓

Python

```
... Final point: -1.8457205408261639
    Suffix averaged point: -1.8522282693631102
    Improvement: 0.006507728536946367
    Optimal: -1.85727503
```

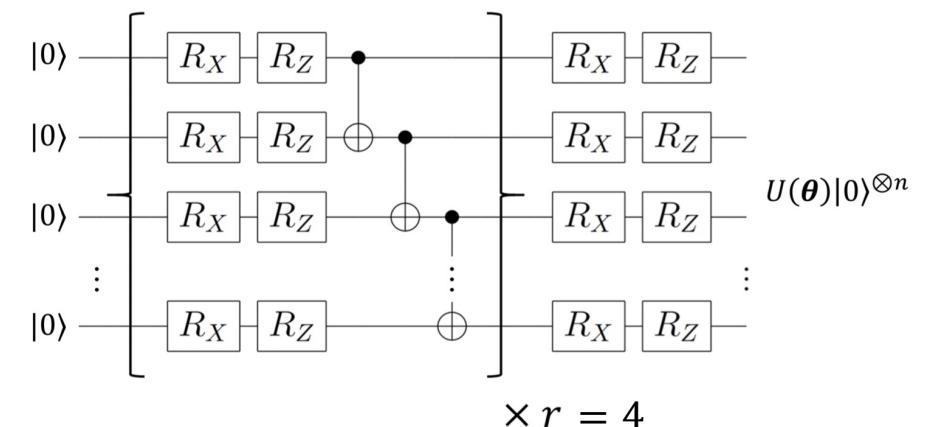
Numerical experiments: setups

- Model

- H₂ molecule
- Transversal-field Ising model (TFIM) with open boundary condition

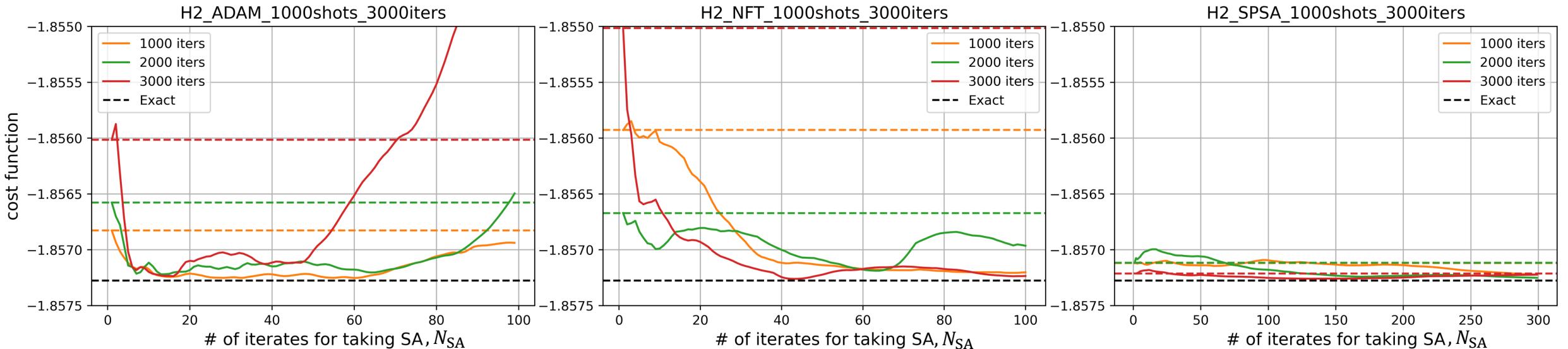
$$H = -J \sum_{i=1}^{n-1} Z_i Z_{i+1} - g \sum_{i=1}^n X_i \quad \text{where } n = 4, 6$$

- Two local ansatz
- ADAM, Nakanishi-Todo-Fujii (NFT) method, SPSA
- Use Noiseless simulator
- Consume 1000 shots for estimating each expectation value, and run 3000 iterations in total.



$$\partial_i f(\boldsymbol{\theta}) \sim f\left(\boldsymbol{\theta} + \frac{\pi}{4} \mathbf{e}_i\right) - f\left(\boldsymbol{\theta} - \frac{\pi}{4} \mathbf{e}_i\right)$$

Numerical experiments 1: H₂ molecule



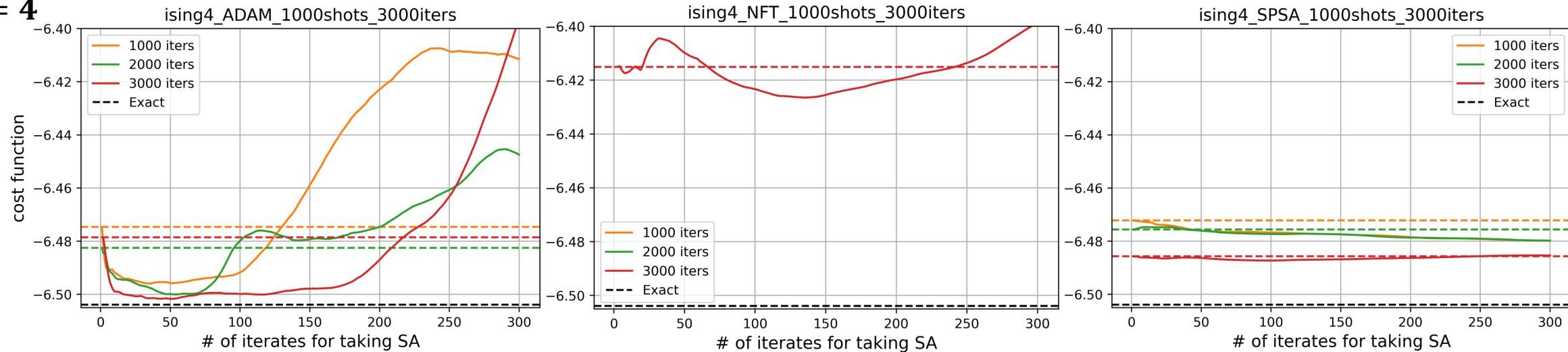
For suffix averaging N_{SA}



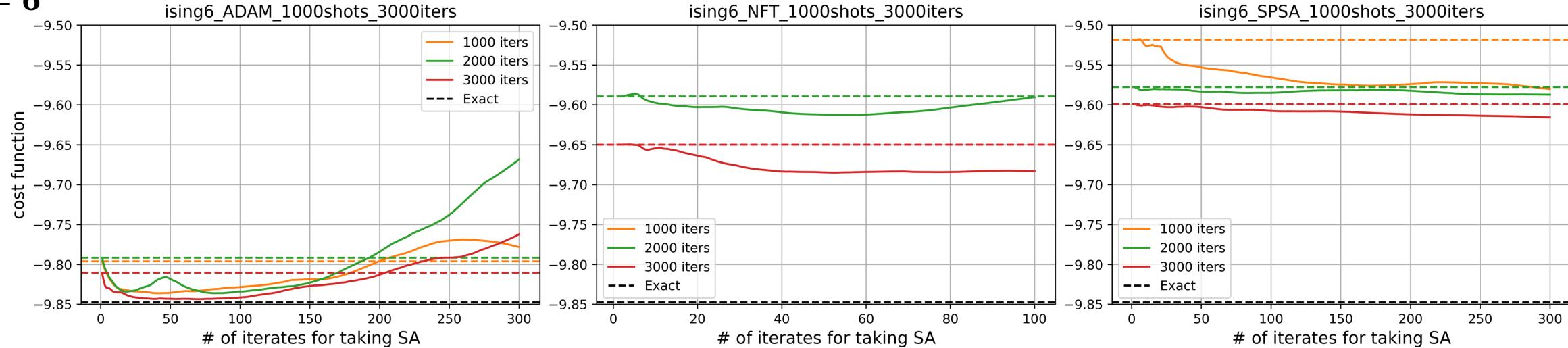
- Suffix averaging improves the final output in VQE of H₂ molecule.
- Significant improvements are achieved in the case of ADAM and NFT.

Numerical experiments 2: TFIM with $n = 4, 6$

$n = 4$

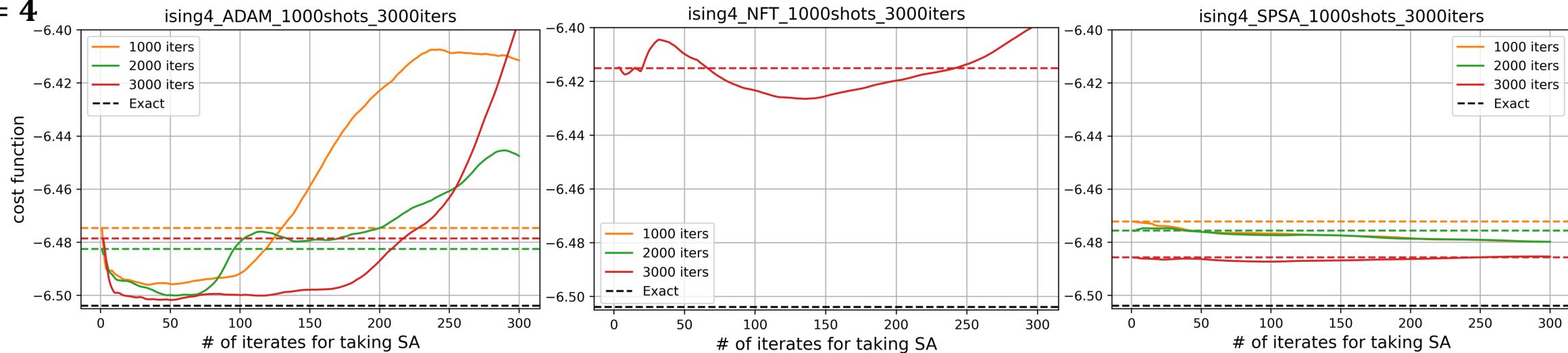


$n = 6$

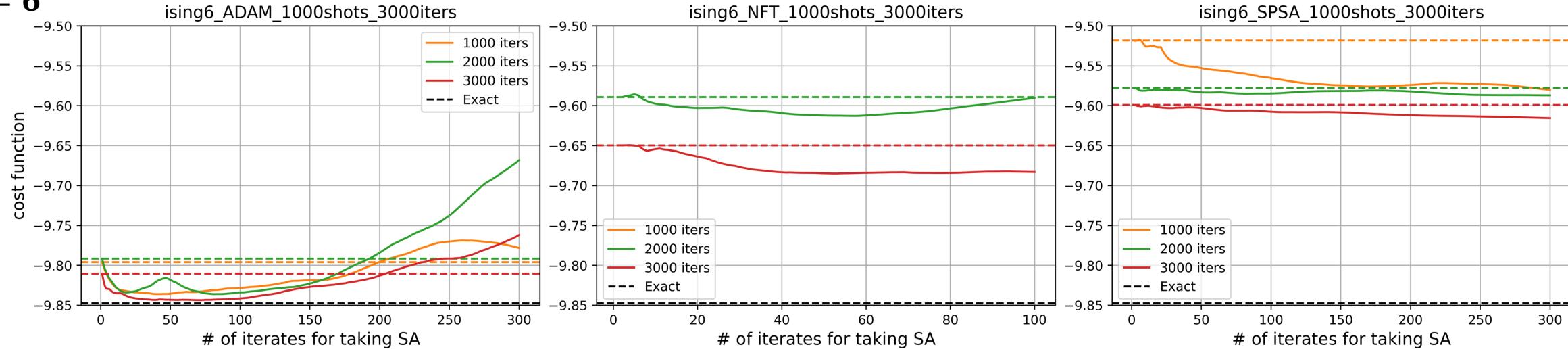


Numerical experiments 2: TFIM with $n = 4, 6$

$n = 4$

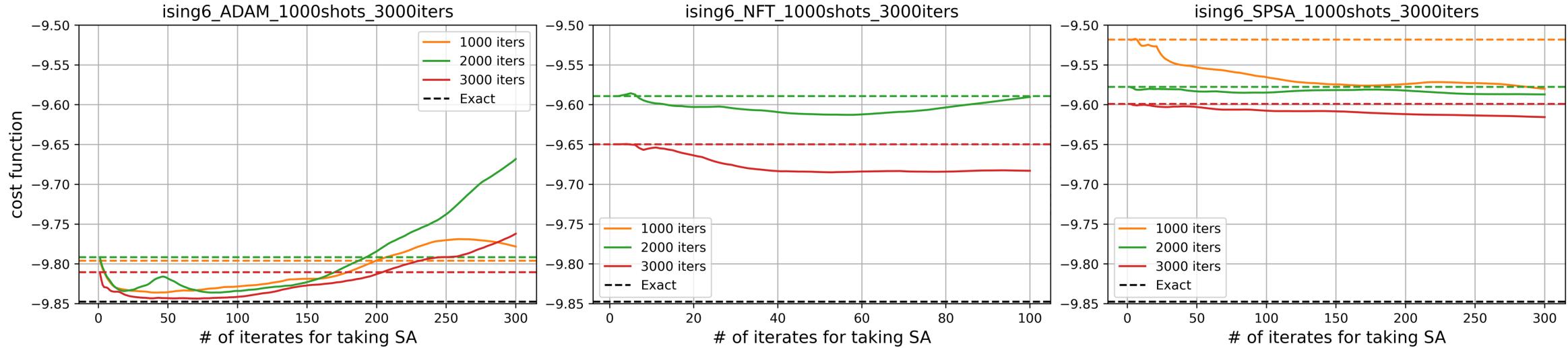


$n = 6$

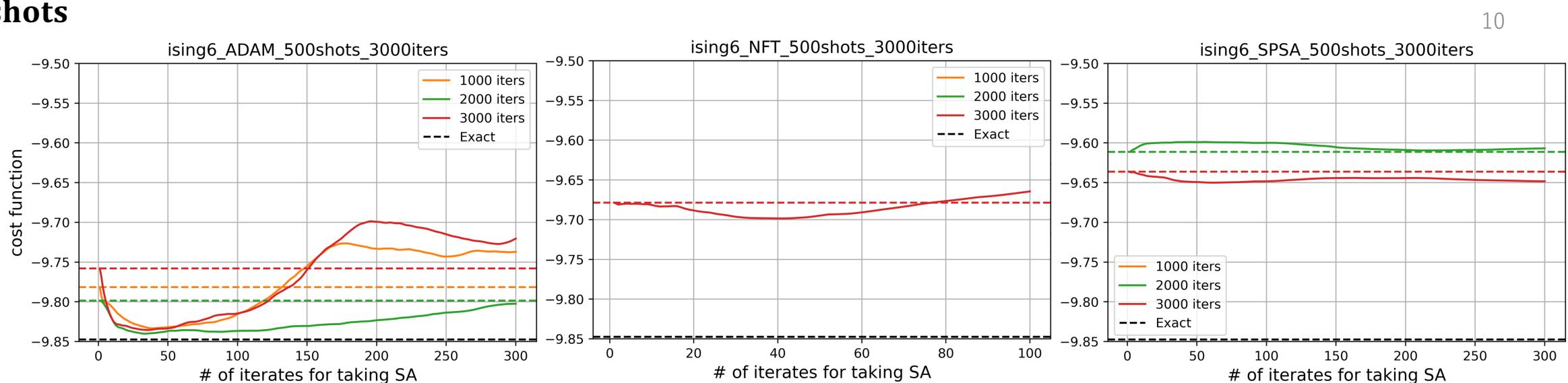


Numerical experiments 2: TFIM with $n = 6$

1000 shots



500 shots

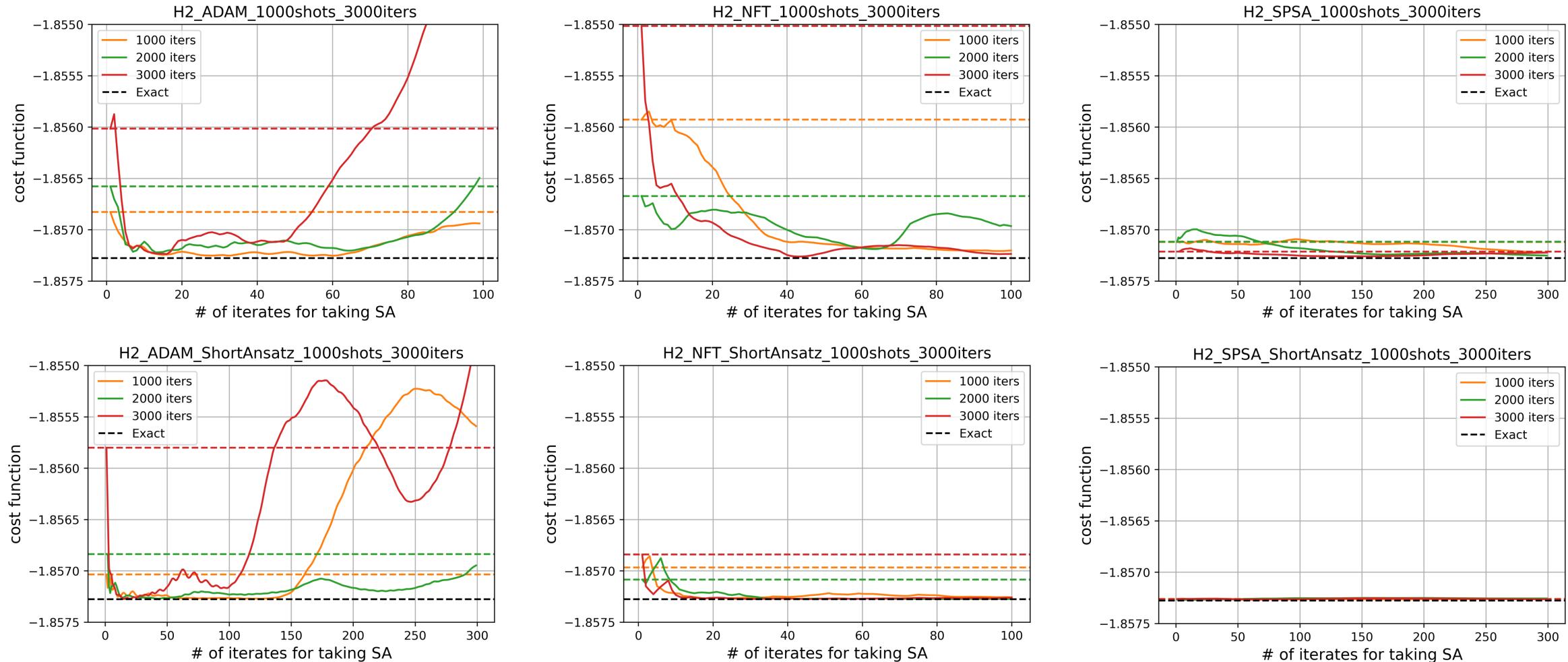


Conclusion

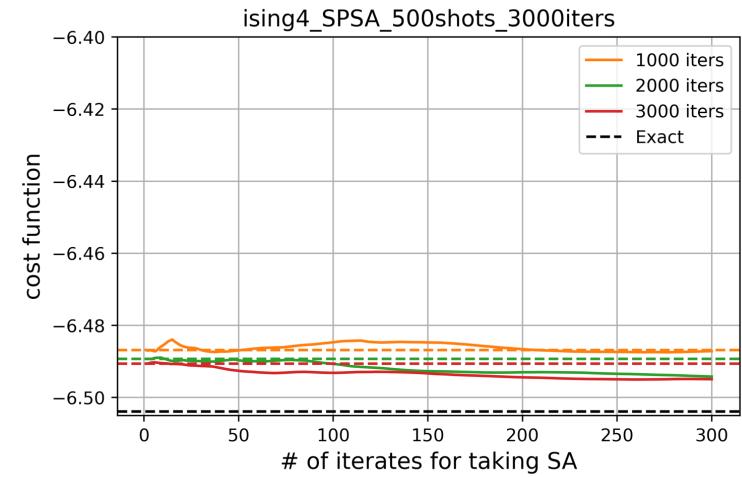
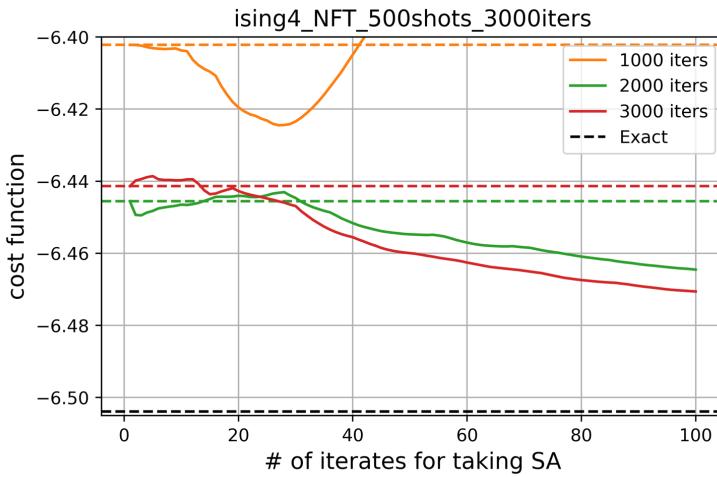
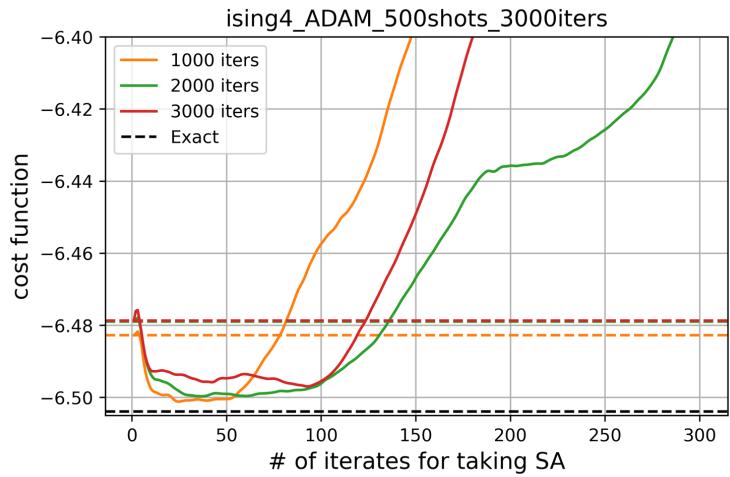
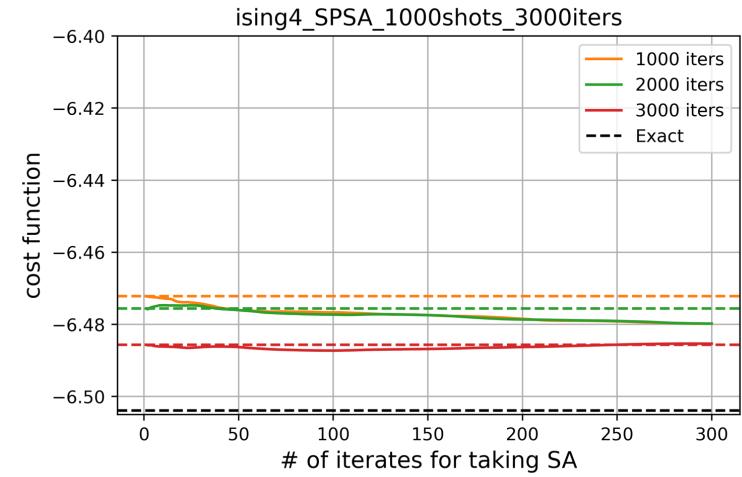
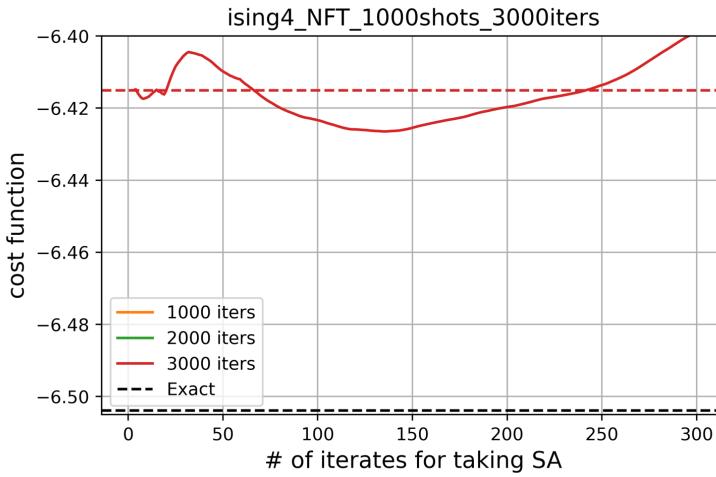
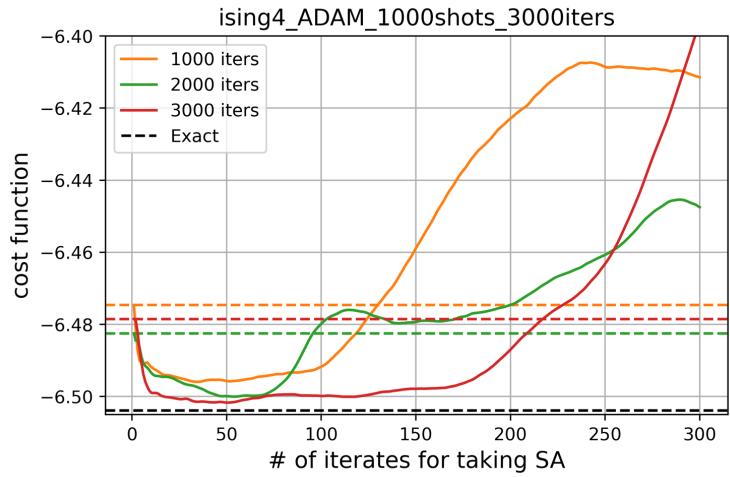
- By taking suffix averaging, we see the improvements of the results of the optimizations in almost every case.
- The advantage of ADAM+suffix averaging is remarkable when the system size increases.
- It is sensitive to the number of points N_{SA} used for suffix averaging.

$N_{SA} = 50$ points may be preferable.

Numerical results 1: H₂ molecule



Numerical results 2: TFIM



Numerical results 3: TFIM

