A QUANTUM-INSPIRED TOOL FOR BRIDGING THE NISQ ERA

Simone Montangero
Investment of 6 M€
National strategic partnerships
Trapped ion quantum computer
ICSC
Centro Nazionale HPC, Big Data e Quantum Computing
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**SUPERCOMPUTING CLOUD INFRASTRUCTURE**

EDUCATION & TRAINING, ENTREPRENEURSHIP, KNOWLEDGE TRANSFER, POLICY, OUTREACH
**Spoke 10 – Quantum Computing**

**WP1. Software (Leader: INFN): Development and application of high-level quantum software for algorithms solving general purpose problems, scientific and industrial applications:** T1.1 New algorithms (Pavia, Bologna, IIT, Catania, CINECA, CNR, Pisa, Sapienza, Bari, Polimi, Padova); T1.2 Applications and use cases (IIT, Bologna, CINECA, CNR, INAF, INFN, Pavia, Pisa, Bari, Bicocca, Polimi, Padova)

**WP2. Mapping, compilation and quantum computing emulation (Leader: CINECA): Development of software toolchain for compilation, benchmarking, verification, emulation of quantum computers and algorithms:** T2.1 Mapping and compilation (Bologna, CNR, Pisa, Polimi); T2.2 Emulation (CINECA, INAF, Bari, Padova)

**WP3. Firmware and hardware platforms (Leaders: CNR, Catania): Development of low-level software for the physical operation of quantum computers. Development and support of the quantum computer hardware chain:** T3.1 Photonic (Sapienza, CNR, Bicocca, Pavia, Napoli); T3.2 Superconducting circuits (Napoli, INFN, Bicocca, CNR, Catania); T3.3 Atoms (CNR, Padova); T3.4 Ions (Padova, CNR); T3.5 Models and firmware (Catania, Polimi, Bari, Padova, Bicocca, CNR, Pisa)
PASQuanS
Programmable Atomic
Large-Scale Quantum
Simulation

Pilot Project
2018-2022

FPA - PASQUANS2
2023-2030

Quantum simulator
with 10000 qubits!
Quantum Computing

- Intro
- Quantum Computing
- QRNG
- Conclusions

Shor algorithm

Order-finding by quantum computer

\[ V_a : |x\rangle |y\rangle \rightarrow |x\rangle |y \oplus a^x \mod N\rangle \]

Circuit model
Quantum Computing

Circuit model

\[ V_\alpha : \ket{x} \ket{y} \rightarrow \ket{x} \ket{y + a^x} \mod N \]

Hybrid (VQE)

Adiabatic - Quantum Annealing
HOW TO GUIDE THE TRANSITION?
HOW TO GUIDE THE TRANSITION?
State of the art in 1D (poly effort)
No sign problem
Extended to open quantum systems
Machine learning
Data compression (BIG DATA)
Extended to lattice gauge theories
Simulations of low-entangled systems of hundreds qubits!


DIGITAL TWIN

Qubit-twin “digital twin”


Many-body digital twin?

Image provided by F. Meinert

DIGITAL TWIN

Hamiltonian description

Optimal control for pulses & gates

Compiler and scheduler

Numerical simulation of many-body system

Quantum Computer Emulators

- Quantum circuits
- Quantum computing Platforms
  - Superconducting, Trapped ions, or neutral atoms

Quantum circuits emulator
- Quantum circuit as a tensor network
- Measurement of local observables
- Efficient sampling of the final state

Digital twin approach
1) Up to 8x8 atoms
2) Schedule native gates
3) Gates as pulses
4) Study crosstalk
5) Run simulation

Comparison and resolve errors per step: GHZ state
GREEN QUANTUM ADVANTAGE

a)

![Graph showing energy vs. system size for different quantum algorithms.]

b)

\[ m = 1 \]

\[ G_{kk'} \]

\[ G_{kk''k'} \] one layer

\[ G_{kk'''} \]

D. Jaschke and SM arxiv:2205.12092
GREEN QUANTUM ADVANTAGE

Equality of Fidelity and Energy Point (EFEP)

(a) 

![Graph showing energy vs. system size with different line types representing exact and two MPS methods.]

(b) 

$m = 1$

---

D. Jaschke and SM arxiv:2205.12092
GREEN QUANTUM ADVANTAGE

Equality of Fidelity and Energy Point (EFEP)

a) Energy $[\text{MJ}]$ vs System size $L$

- Exact
- MPS(1024)
- MPS(4096)

b) $m = 1$

D. Jaschke and SM arxiv:2205.12092
green quantum advantage

**Equality of Fidelity and Energy Point (EFEP)**

\[ E_{\text{EFEP fit}} \]

\[ E_{\text{QPU}} \]

\[ E_{\text{MPS}} \]

\[ E_{\text{Ion[E]}} \]

\[ E_{\text{SC[E]}} \]

\[ E_{\text{Rydb.[T]}} \]

**Figure a)**

Energy [MJ] vs. System size \( L \)

- **Exact**
- **MPS(1024)**
- **MPS(4096)**

**Figure b)**

\[ m = 1 \]

**D. Jaschke and SM arxiv:2205.12092**
When do we really need a quantum simulation/computation?
$$\hat{H} = -t \sum_{x, \mu} \left( \hat{\psi}_x^\dagger \hat{U}_{x, \mu} \hat{\psi}_{x+\mu} + h.c. \right)$$

$$+ m \sum_x (-1)^x \hat{\psi}_x^\dagger \hat{\psi}_x + \frac{g_e^2}{2} \sum_{x, \mu} \hat{E}_{x, \mu}^2$$

$$- \frac{g_m^2}{2} \sum_x \left( \hat{U}_{x, \mu_x} \hat{U}_{x+\mu_x, \mu_y} \hat{U}_{x+\mu_y, \mu_x}^\dagger \hat{U}_{x, \mu_y}^\dagger + h.c. \right)$$

---

**LGT AT FINITE DENSITY**

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**PRX (2020)**
The gauge invariant Hilbert space is thus given by all
\[
\hat{H} = -t \sum_{x, \mu} \left( \hat{\psi}^\dagger_x \hat{U}_{x,\mu} \hat{\psi}_{x+\mu} + h.c. \right) \\
+ m \sum_x (-1)^x \hat{\psi}^\dagger_x \hat{\psi}_x + \frac{g_2}{2} \sum_{x, \mu} \hat{E}_{x,\mu}^2 \\
- \frac{g_m^2}{2} \sum_x \left( \hat{U}_{x,\mu x} \hat{U}_{x+\mu x,\mu y} \hat{U}^\dagger_{x+\mu y,\mu_x} \hat{U}^\dagger_{x,\mu_y} + h.c. \right)
\]

\[\text{Vacuum Phase}\]
\[\text{Charge-Crystal Phase}\]

\[\langle \hat{n} \rangle\]

\[m\]

\[g_2^2/2\]

\[\rho\]

\[\rho_t = 0\]

\[L = 2\]

\[L = 4\]

\[L = 8\]

Hilbert space of
\(~64 \times 64 \times 64\) qubits!

200 Kb QRAM

PRX (2020)

Nature Comm. (2021)
ENTANGLEMENT GENERATION IN QED SCATTERING PROCESSES

ENTANGLEMENT GENERATION IN QED SCATTERING PROCESSES

\[ S(T, g, x) \]

\[ S(T, g, x) \]

\[ \frac{\hbar}{m} \left( T - T_0 \right) \]

\[ S(T, g, x) - S(T_0, x) \]

\[ \text{position } x \]

\[ \text{position } x \]

\[ \text{position } x \]

\[ \text{position } x \]

Universal Scaling Relation?
TENSOR NETWORK MACHINE LEARNING

T. Felser et al. Npj Quantum Information (2021)
RADIOThERAPY PLAN OPTIMIZATION

(a) OAR tumor

(b) IMRT beam

(c) Beamlet

(d) $\theta_1, \theta_2, \ldots, \theta_N$

(e) $\min_{x_1, \ldots, x_{NB}} F(\tilde{x})$

Beam angles selection

Dose matrices calculation

Plan optimization

Mapping to Ising

Ground-state search

Read-out and decoding
INDUSTRY APPLICATIONS

Mission planning for earth observation

- Geographical feasibility refinement
- SAR Parameters calculation

Hard optimization problems

- Combinatorial optimization (Knapsack problem)
- From single satellite to constellations

- Identification of use cases in the field of mission planning
- Estimate (hybrid) QPU-specs for realistic problems
RESEARCH LINES

Classical simulations and methods

Theoretical development and analysis

Quantum computer emulation

Experiment benchmarking, support and optimisation

Science

Generation and manipulation of Schrödinger cat states in Rydberg atom arrays

Remote optimization of an ultracold atoms experiment by experts and citizen scientists
Remote optimization of an ultracold atoms experiment by experts and citizen scientists
Tensor network algorithms can be used to benchmark, verify, support and guide quantum simulations, computations and communication.

Hybrid solutions will give the first results in
CONCLUSIONS

➤ Tensor network algorithms can be used to benchmark, verify, support and guide quantum simulations, computations and communication

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➤ Complex optimisation problems
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➤ Hybrid solutions will give the first results in

➤ Complex optimisation problems
➤ Machine learning
➤ Quantum sensing
Tensor network algorithms can be used to benchmark, verify, support and guide quantum simulations, computations and communication.

Hybrid solutions will give the first results in

- Complex optimisation problems
- Machine learning
- Quantum sensing
- Optimized protocols
Thank you for your attention!

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