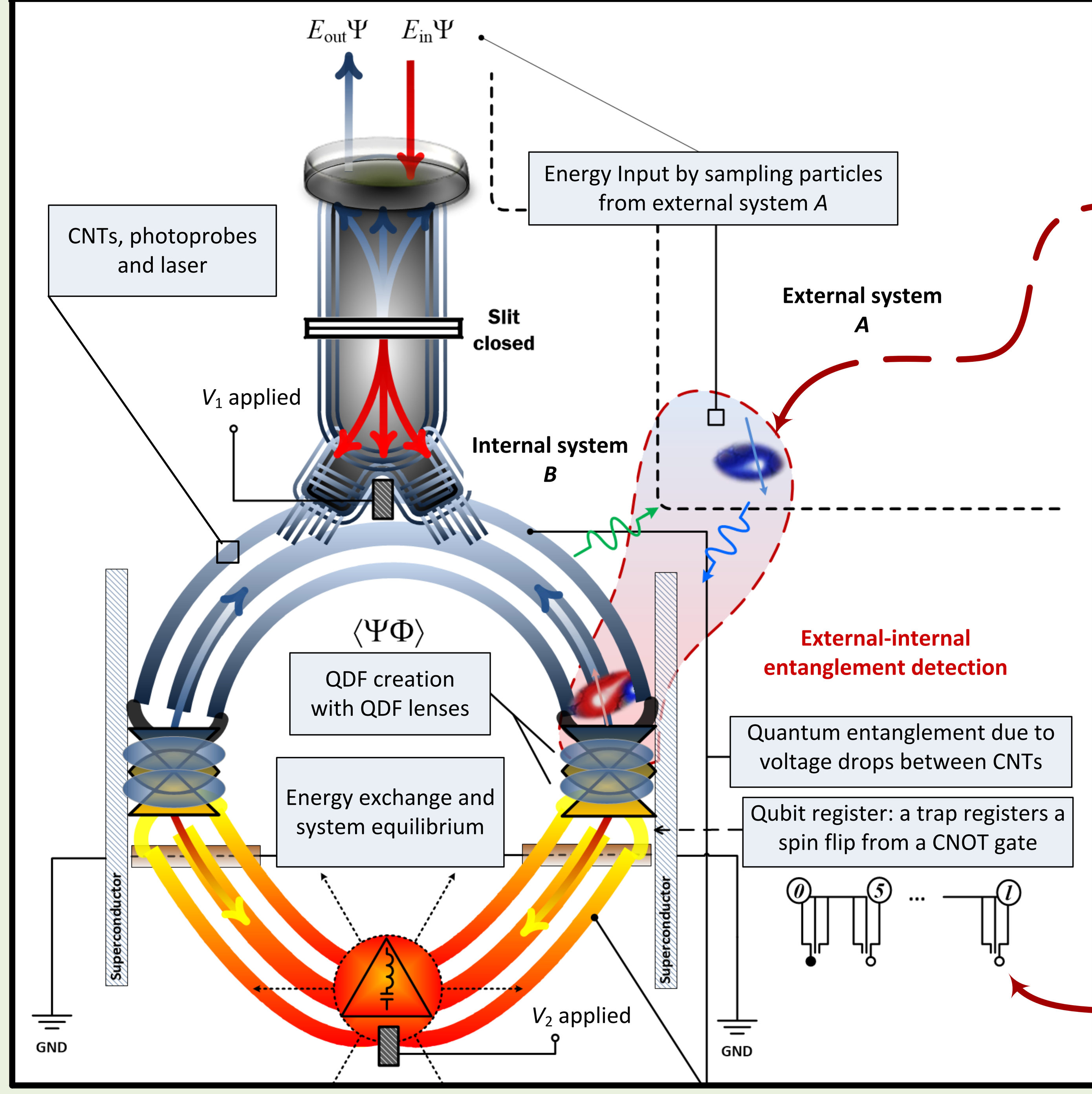
Physical INPUTS



Simulate or build a QDF thermodynamic system based on the QDF theoretic model and application via lenses and nanomaterials like CNT 2016 – 2020

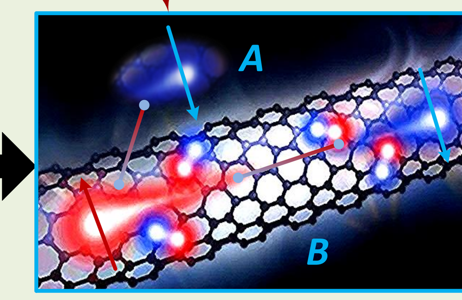
QDF COMPUTATIONAL METHOD: simulates QDF system's lenses, sensors, photonic probes and nanomaterials that cause events as an ST or PT. A GS or ES field is transformed into a QDF from a particle pair e.g., entangled BEC pairs. System measurement outcome data are generated by a QF-LCA or a QDF circuit as a qubit code or encoded quantum states. The QF-LCC decodes the registered and classified qubit code to determine their probability space in doubling, occupation, correlation and information. The QDF circuit measurement outcome as the expected value of the particle state in the system develops a strong prediction model.

Closed Heat Engine (System)

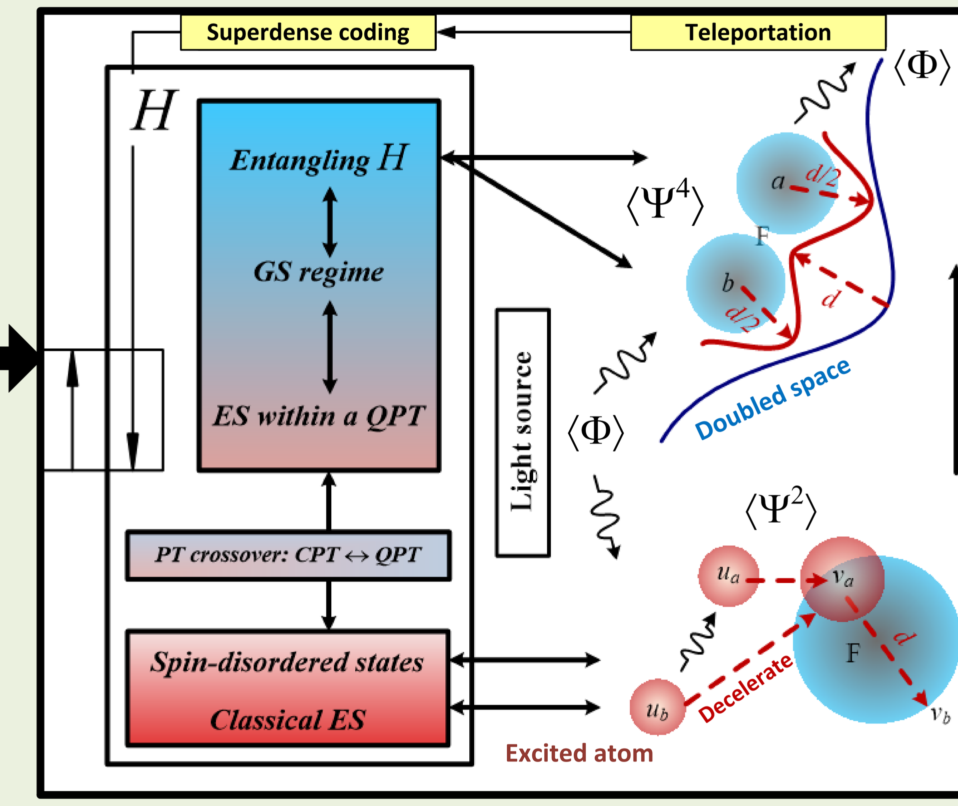
Systems *A* & *B* State Readout

Observer externally records events and samples on micro and nanoscales for user(s) from the QDF circuit

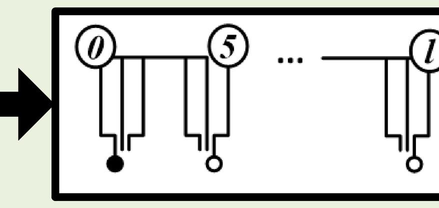
QDF circuit tested on *N*-qubit machines prior



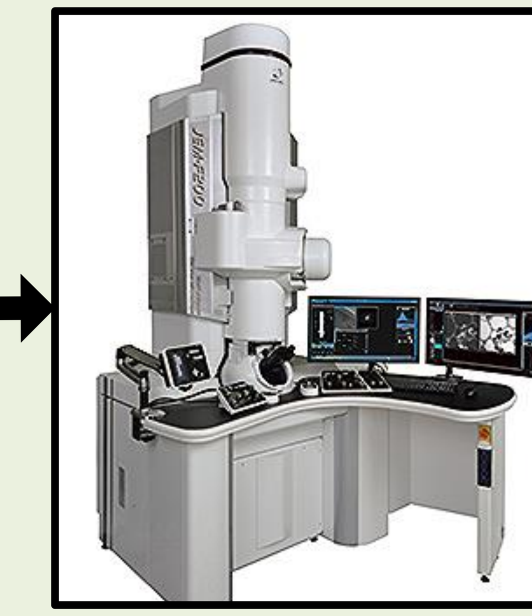
Observe quantum events and energy exchange between pairwise particles of the external and internal systems *A* and *B* via QDF lenses and CNTs



Left: the Hamiltonian entangles as events evolve by PTs between ESs and GSs cyclically;
Lower-right: a single field of a particle out of $N \geq 2n$ sampled particles from an ES into a BEC;
Upper-right: a QDF is created as an entangled EPR BEC pair in quantum communication
2018 – 2022



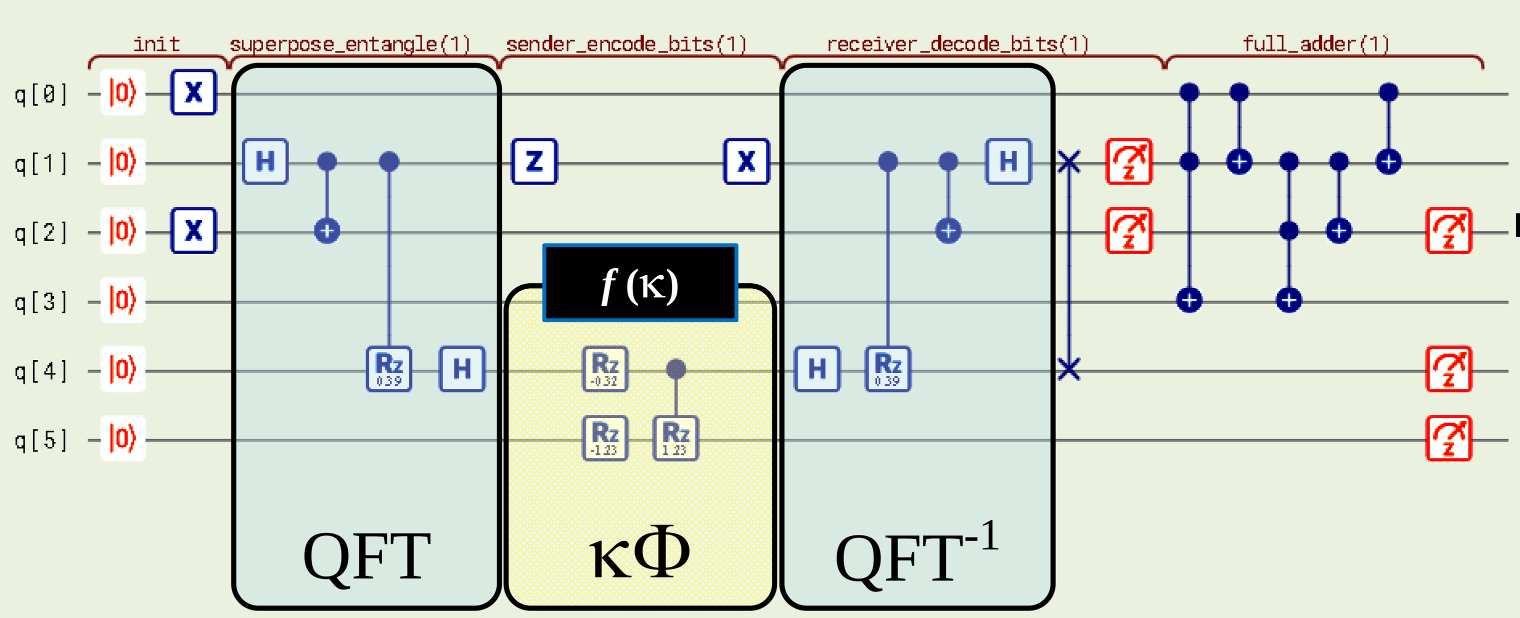
QDF Lens distance based CNOT circuit in system *B* to count registered qubits to output QDF data as a QF-LCA



Observer analyzes and determines double probability outcomes of events; then trains the QDF circuit for strong event predictions 2020 - 2022

Physical + Software OUTPUTS

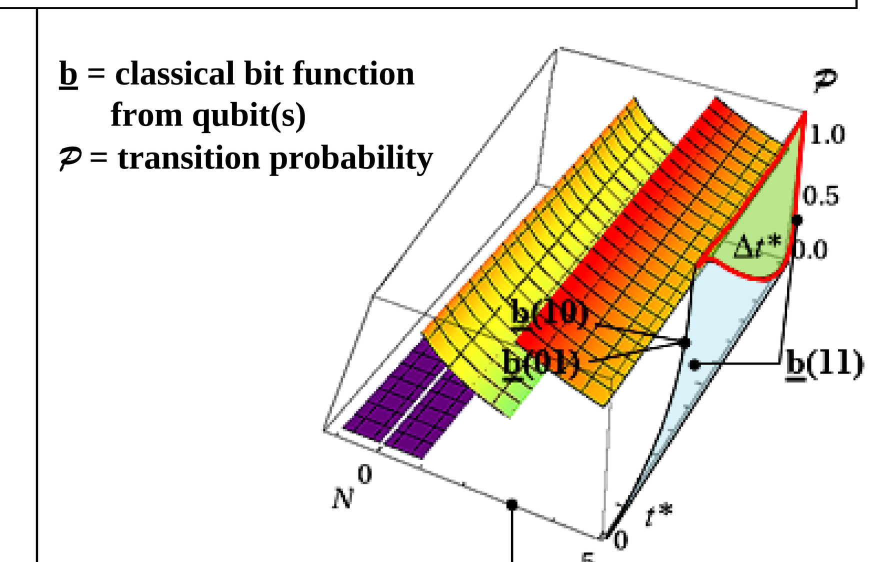
QDF circuit's energy in/out via QDF scalar transform for $N \geq 3$ particles; QDF is compatible with QFT and its inverse QFT^{-1} per measurement



IN → Scalar κ function → OUT

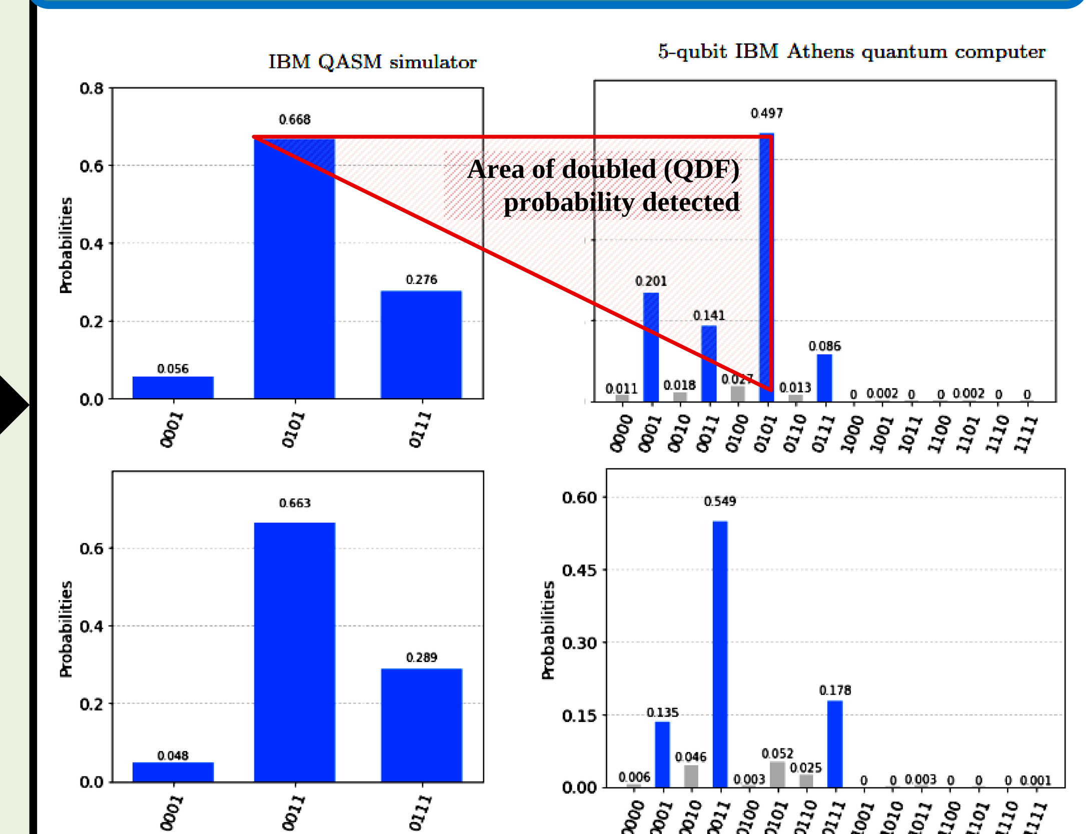
Circuit measurement outcome at the Encoding Level for $N \geq 3$ particles, predicting QDF $\mathcal{P}$'s

For $n \geq 3$, the expected outcome is $\underline{b}(\{01, 10\})$ with a $\mathcal{P} \geq 2/3$, and $\underline{b}(11)$ with a $\mathcal{P} \leq 1/3$ predicted for any case without a SWAP gate



For $n \geq 3$, the expected outcome is $\underline{b}(01)$ with a $\mathcal{P} \geq 2/3$, and $\underline{b}(\{10, 11\})$ with a $\mathcal{P} \leq 1/3$ predicted for any case with a SWAP gate

Decoding measurement outcome as code samples with their p's for $N \geq 1$ particle pairs



Analyzed OUTPUTS by QF-LCA

OBSERVER OUTPUTS:

- A quantum (light-particle) heat engine sampled particles from system *A*
- The heat engine entangled sampled particles at ultracold temperatures
- Entanglement was registered as qubits to predict a system state by:
- A QDF was formed doubling particle space in probability to its position
- A QDF provided information from entangled particles exchanged in the system
- Particle spin and position predicted by sharing the QDF information as qubits
- Qubits counted in a QDF coding system predicting states with high probability
- A QDF extra qubit complemented the information on a hidden particle state
- QDF circuit found the hidden state relative to thermal events in the system

QAI Decision-making by QF-LCC within QF-LCA

- Obtain efficient heating or cooling of particles by using information above by:
- create or reroute energy paths for those particles not participating in a thermal event in system *A* to participate by focusing/defocusing the distribution of their states through QDF lenses in system *B*

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ACRONYMS:

PT = phase transition
Q = quantum, C in CPT = classical
QDF = quantum double-field
QF-LCA = QDF lens coding algorithm
BEC = Bose-Einstein condensate
QAI = quantum artificial intelligence
QFT = quantum Fourier transform
QF-LCC = QDF lens coding classification
CNT = carbon nanotube
ES = excited state
GS = ground state

CONCLUSION:

The QF-LCA when trained as a QAI algorithm makes strong predictions after the expected e.g., 2/3 from 1/3 probability value, to values close to 1 probability or near zero entropy as the system evolves in rerouting energy paths making particles that have not been participating in a thermal event (combustion or refrigeration) to participate and contribute to greater system efficiencies.