

Abstract: This work proposes the Generalized Quantum-Inspired Evolutionary Algorithm (GQIEA). Like QIEA, GQIEA is also based on the quantum computing principle of superposition of states, but extends it not only to be used for binary values (0, 1), but for any finite set of values $(1, 2, \dots, n)$. GQIEA also defines a generalized Q-gate operator, which is a variation operator to drive the individuals toward better solutions. To verify GQIEA effectiveness and applicability, this is applied to the Assignment and Knapsack Problems. Results show that GQIEA has a good performance, even with a small population.

QIEA

QIEA [Han, 2002], is an Evolutionary Algorithm composed by individuals composed by Q-bits, an evaluation function, and a population dynamic. Instead classical evolutionary algorithm, this model uses:

- An updating operator called Q-gate.
- An observation process.

Representation:

A Q-bit is the smallest unit of information in QIEA, which is defined using a pair of numbers (α, β) as shown in equation 1.

$$\begin{bmatrix} \alpha \\ \beta \end{bmatrix} \quad (1)$$

where the following identity is satisfied:

$$|\alpha|^2 + |\beta|^2 = 1$$

A Q-bit individual consists of a Q-bits string defined as Eq. 2.

$$\begin{bmatrix} \alpha_1 & \alpha_2 & \dots & \alpha_m \\ \beta_1 & \beta_2 & \dots & \beta_m \end{bmatrix} \quad (2)$$

The population updating is performed by **Q-gate**. This operator is defined as a rotation matrix of Eq. 3.

$$U(\Delta\theta_i) = \begin{bmatrix} \cos(\Delta\theta_i) & -\sin(\Delta\theta_i) \\ \sin(\Delta\theta_i) & \cos(\Delta\theta_i) \end{bmatrix} \quad (3)$$

applied to every column of the quantum individual \mathbf{q}_i and ensuring compliance of the identity $|\alpha'_k|^2 + |\beta'_k|^2 = 1$

QQIEA

The proposed Quantum-Inspired Evolutionary Algorithm instead a Q-bit uses a generalized Q-bit (GQ-bit):

Representation: A generalized Q-bit is defined as a n -uple, where n is the number of possible observed states $|S|$ of the GQ-bit, as shown in Eq. 4.

$$\begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix} \quad (4)$$

and a GQ individual is a GQ-bits string of the Eq. 5.

$$\begin{bmatrix} \alpha_{1,1} & \alpha_{1,2} & \dots & \alpha_{1,m} \\ \alpha_{2,1} & \alpha_{2,2} & \dots & \alpha_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{n,1} & \alpha_{n,2} & \dots & \alpha_{n,m} \end{bmatrix} \quad (5)$$

GQ-gate: GQIEA also defines a GQ-gate operator.

A j -th GQ-bit of a GQ-bit represents the superposition of n states $S = \{s_1, s_2, \dots, s_n\}$. Let the state s_ϕ be the observed state on best individual, then the new α 's of the GQ-bit will be determined as follows:

Arithmetic GQ-gate:

$$\alpha_i = \begin{cases} \alpha_i + \Delta_t & \text{if } i = \phi \\ \alpha_i & \text{if } i \neq \phi \end{cases}, \quad i = 1, 2, \dots, n \quad (6)$$

Geometric GQ-gate:

$$\alpha_i = \begin{cases} \alpha_i \cdot \Delta_t & \text{if } i = \phi \\ \alpha_i & \text{if } i \neq \phi \end{cases}, \quad i = 1, 2, \dots, n \quad (7)$$

A normalization is done after α_i updating, to ensure $\sum_i \alpha_i = 1.0$

Case Studies

Bounded Knapsack Problem [Kereller, 2004]: Tests performed over the KP generalized version: Bounded Knapsack problem, like KP but allowing several copies of the same k object, limited by maximum m_k , as Eq. 8:

$$\max \sum_{\forall k \in K} v_k x_k, \quad x_k \in \{0, 1, \dots, m_k\}, \quad \text{such that } \sum_{\forall k \in K} w_k x_k \leq W \quad (8)$$

Obtained Results:

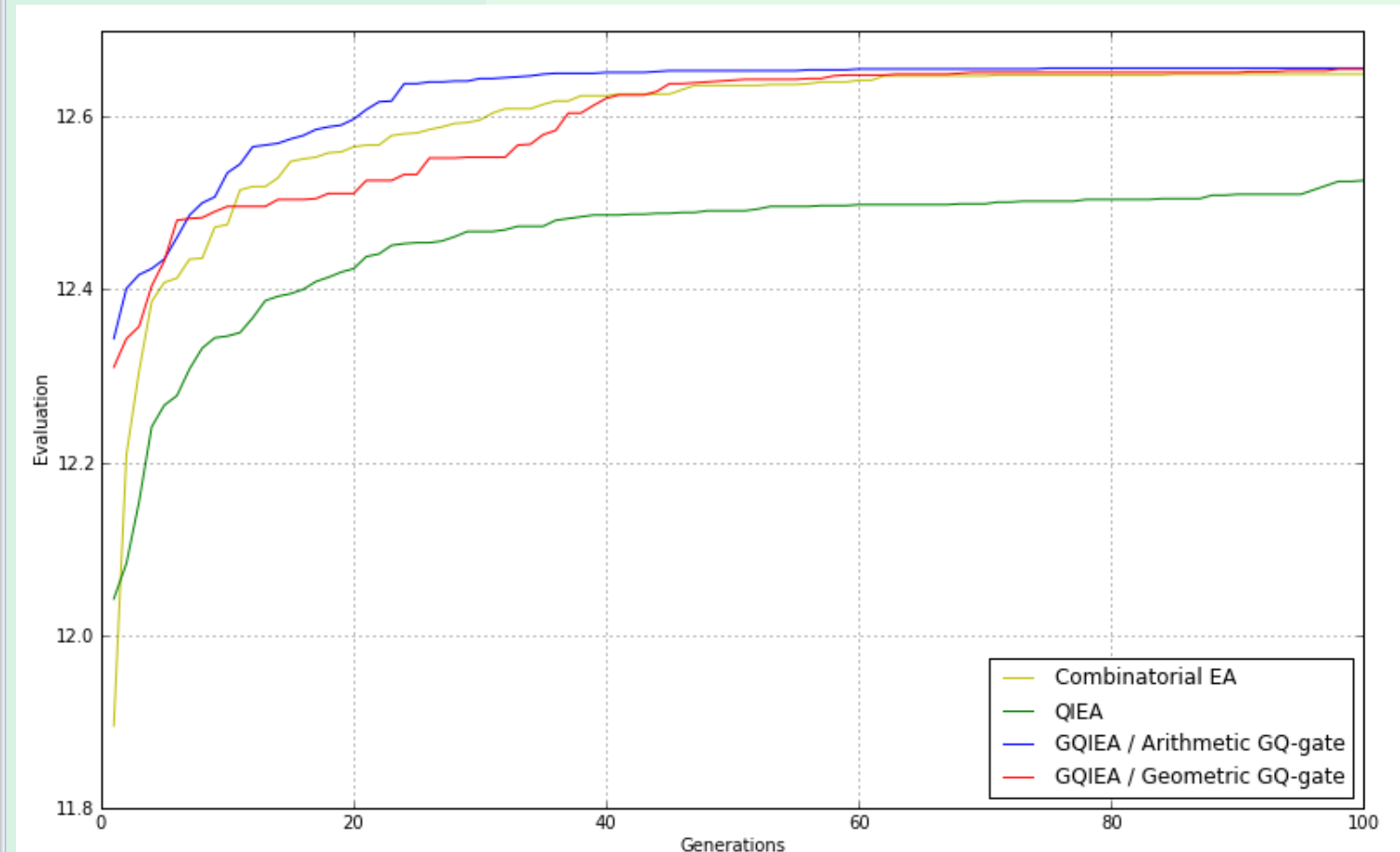


Figure 1: Comparison of an average of 10 executions of the Combinatorial EA, the QIEA and the GQIEA, applied to the Bounded Knapsack Problem.

Algorithm	Result	Runtime
Combinatorial EA	12.65	145.962 s
QIEA	12.51	49.924 s
GQIEA (Arithmetic QGate)	12.65	31.970 s
GQIEA (Geometric QGate)	12.65	36.970 s

Table 1: Results of the algorithms applied to the Bounded Knapsack Problem

- GQIEA (both GQ-gates) and CEA reach the same final result, QIEA was left behind.
- GQIEA was faster than combinatorial EA (slowest runtime) and QIEA, by dimensionality reduction.

Conclusions

- A new more generally evolutionary model was proposed. The individuals representation allows superposition of solutions in any set of finite states, to improve the performance of QIEA in combinatorial optimization problems.
- Two updating operators were proposed: arithmetic GQ-gate and geometric GQgate.
- The GQIEA was compared against the Combinatorial EA and original QIEA. Outcomes show that the GQIEA outperforms other algorithms in results quality and convergence.

References

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