TABLE I. Detailed comparison with SOTA algorithms for each of the five index data sets and on seven different performance indicators described in Appendix A2. Entries in red correspond to cases where TN-GEO performed better or tied compared to the other algorithm. Entries in **bold**, corresponding to the best (lowest) value, for each specific indicator.

Data Set	Performance Indicator	GTS	IPSO	IPSO-SA	PBILD	GRASP	ABCFEIT	HAAG	VNSQP	RCABC	TN-GEO
Hang Seng	Mean	1.0957	1.0953	-	1.1431	1.0965	1.0953	1.0965	1.0964	**1.0873**	1.0958
	Median	1.2181	-	-	1.2390	1.2155	1.2181	1.2181	1.2155	**1.2154**	1.2181
	Min	-	-	-	-	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**
	Max	-	-	-	-	**1.5538**	**1.5538**	**1.5538**	**1.5538**	**1.5538**	**1.5538**
	MEUCD	-	-	**0.0001**	-	**0.0001**	**0.0001**	**0.0001**	**0.0001**	**0.0001**	**0.0001**
	VRE	-	-	1.6368	-	1.6400	1.6432	1.6395	1.6397	**1.6342**	1.6392
	MRE	-	-	0.6059	-	0.6060	0.6047	0.6085	0.6058	**0.5964**	0.6082
DAX100	Mean	2.5424	2.5417	-	2.4251	2.3126	2.3258	2.3130	2.3125	**2.2898**	2.3142
	Median	**2.5466**	-	-	2.5866	2.5630	2.5678	2.5587	2.5630	2.5629	2.5660
	Minimum	-	-	-	-	0.0059	0.0023	0.0023	0.0059	0.0059	**0.0023**
	Maximum	-	-	-	-	**4.0275**	**4.0275**	**4.0275**	**4.0275**	**4.0275**	**4.0275**
	MEUCD	-	-	**0.0001**	-	**0.0001**	**0.0001**	**0.0001**	**0.0001**	**0.0001**	**0.0001**
	VRE	-	-	6.7806	-	6.7593	6.7925	6.7806	6.7583	6.8326	**6.7540**
	MRE	-	-	1.2770	-	1.2769	1.2761	1.2780	1.2767	**1.2357**	1.2763
FTSE100	Mean	1.1076	1.0628	-	0.9706	0.8451	0.8481	0.8451	0.8453	**0.8406**	0.8445
	Median	**1.0841**	-	-	**1.0841**	**1.0841**	**1.0841**	**1.0841**	**1.0841**	**1.0841**	**1.0841**
	Minimum	-	-	-	-	0.0016	0.0047	**0.0006**	0.0045	0.0016	0.0047
	Maximum	-	-	-	-	**2.0576**	2.0638	2.0605	2.0669	2.0670	2.0775
	MEUCD	-	-	**0.0000**	-	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**
	VRE	-	-	2.4701	-	2.4350	2.4397	2.4350	2.4349	**2.4149**	2.4342
	MRE	-	-	0.3247	-	0.3245	0.3255	**0.3186**	0.3252	0.3207	0.3254
S&P100	Mean	1.9328	1.6890	-	1.6386	1.2937	1.2930	1.2930	**1.2649**	1.3464	1.2918
	Median	1.1823	-	-	1.1692	1.1420	1.1369	**1.1323**	**1.1323**	1.1515	1.1452
	Minimum	-	-	-	-	0.0009	**0.0000**	**0.0000**	**0.0000**	0.0009	**0.0000**
	Maximum	-	-	-	-	5.4551	**5.4422**	5.4642	5.4551	5.4520	5.4422
	MEUCD	-	-	**0.0001**	-	**0.0001**	**0.0001**	**0.0001**	**0.0001**	**0.0001**	**0.0001**
	VRE	-	-	2.6281	-	2.5211	2.5260	2.5255	**2.5105**	2.5364	2.5269
	MRE	-	-	0.7846	-	0.9063	0.8885	**0.7044**	0.9072	0.8858	0.9117
Nikkei	Mean	0.6066	0.6870	-	0.5972	0.5782	0.5781	0.5781	0.5904	**0.5665**	0.5793
	Median	0.6093	-	-	0.5896	0.5857	0.5856	0.5854	0.5857	0.5858	0.5855
	Minimum	-	-	-	-	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**
	Maximum	-	-	-	-	**1.1606**	**1.1606**	1.1607	**1.1606**	**1.1606**	**1.1606**
	MEUCD	-	-	0.0000	-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	VRE	-	-	0.9583	-	0.8359	0.8396	**0.8191**	0.8561	0.8314	0.8353
	MRE	-	-	1.7090	-	0.4184	0.4147	0.4233	0.4217	**0.4042**	0.4229

TABLE II. Pairwise comparison of TN-GEO against each of the SOTA optimizers. The asymptotic significance is part of the Wilcoxon signed-rank test results. The null hypothesis that the performance of the two algorithms is the same is tested at the 95% confidence level (significance level: $\alpha = .05$). Results show that TN-GEO is on par with all the SOTA algorithms, and in two cases, GTS and PBILD, it significantly outperforms them. We also report the count for TN-GEO wins, losses, and ties, compared to each of the other algorithms.

TN-GEO vs Other:	GTS	IPSO	IPSO-SA	PBILD	GRASP	ABCFEIT	HAAG	VNSQP	RCABC
Wins(+)	6	4	6	9	12	10	11	11	8
Loss(-)	2	1	4	0	12	9	11	12	16
Ties	2	0	5	1	11	16	13	12	11
(Wins+Ties)/Total	80%	80%	67%	100%	66%	74%	69%	66%	54%
Asymptotic significance (p)	.036	.080	.308	.008	.247	.888	.363	.594	.110
Decision	Reject	Retain	Retain	Reject	Retain	Retain	Retain	Retain	Retain

TABLE III. State-of-the-art (SOTA) algorithms used in the comparison with our proposal, TN-GEO.

Acronym	Algorithm	Paper
GTS	Genetic algorithm, tabu search and simulated annealing algorithms.	Chang, et al., 2000 [1]
IPSO	An Improved Particle Swarm Optimization.	Deng, et al., 2012 [2]
IPSO-SA	An Improved Particle Swarm Optimization with simulated annealing.	Mozafari, M., 2011 [3]
PBILD	A population-based incremental learning and differential evolution algorithms.	Lwin & Qu, 2013 [4]
GRASP	A greedy randomized adaptive search procedure.	Baykasoglu et al., 2015 [5]
ABCFEIT	An artificial bee colony algorithm with feasibility enforcement and infeasibility toleration.	Kalayci et al., 2017 [6]
HAAG	A hybridization of ant Colony, artificial Bee Colony and genetic algorithms.	Kalayci et al., 2020 [7]
VNSQP	A variable neighborhood search algorithm with quadratic programming.	Kalayci et al., 2020 [8]
RCABC	A rapidly converging Artificial Bee Colony Algorithm.	Cura, 2021 [9]
TN-GEO	Our proposed quantum-enhanced optimization	

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