Quantum Paradigm in Energy Systems: Architecture of the "Quantum-Nuclear Nexus" System

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Abstract: - Nuclear power plant operational data represent an underutilised source of information for investment decision-making. This paper examines that relationship through the development of the Quantum-Nuclear Nexus (QNN). The proposed architecture is organised into three functional layers: data acquisition from nuclear facilities and financial markets, application of artificial intelligence methods and quantum-inspired optimisation, and order execution via the QuantConnect platform. Physical reactor parameters are used as input signals for a decision model implemented in Python, with portfolio optimisation formulated as a QUBO problem and solved using simulated annealing. Optimisation is currently performed using quantum-inspired heuristics on classical hardware. The architecture is designed for future deployment on quantum processors, though no quantum hardware was used in this study and no quantum advantage is claimed.

Key-Words: - quantum infrastructure, nuclear energy, hybrid optimization, QuantConnect, portfolio management, energy systems.

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1 Introduction

This paper starts from the premise that reactor operational parameters — such as capacity availability, generation stability, and planned outages — may indirectly affect energy markets and the business performance of energy companies. Modern power grids are complex systems in which energy production and financial markets are tightly interconnected [1], yet their interdependence is rarely analysed within a single unified model. The aim of this paper is to demonstrate how data from nuclear facilities can serve as a useful source of information for investment decision-making.

Nuclear power plants provide stable baseload electricity generation independently of weather and climate conditions, making them a key factor in energy security, [2]. Unlike intermittent renewables, nuclear plants operate at high capacity factors with predictable fuel costs, contributing to the stability and reliability of diversified energy portfolios. Nevertheless, the financial valuation and operational risk management in the nuclear sector remain insufficiently investigated using advanced computational methods.

Quantum algorithms have shown promising results in solving complex power-dispatch problems in electrical grids, though practical advantages over classical approaches remain an active area of research, [3]. Platforms such as QuantConnect, on the other hand, already enable the development and testing of data-driven strategies, [4]. Integrating these capabilities with nuclear reactor data of enabling an analytical system that simultaneously tracks physical and financial risks.

The Quantum-Nuclear Nexus (QNN) is a three-layer hybrid ecosystem comprising a data-acquisition layer, an intelligence layer (AI and quantum algorithms), and an execution layer implemented on the QuantConnect platform. The system is validated through a three-month backtesting simulation based on real market data, directly linking reactor operational state to portfolio-rebalancing decisions and providing initial evidence of system responsiveness and drawdown reduction under adverse market conditions. The result should be interpreted as preliminary given the short evaluation period. The long-term assessment is based on data from 2025, a period of pronounced market volatility.

2 Theoretical Background

2.1 Nuclear Energy and Power Grid Stability

Nuclear energy accounts for approximately 10% of global electricity generation. Due to its low carbon-dioxide emissions during operation, it is recognised as a significant energy source in decarbonisation strategies for the energy sector, [5]. Unlike intermittent renewables, nuclear plants operate at high capacity factors with predictable fuel costs, contributing to the stability and reliability of the energy system, [6]. The nuclear sector faces numerous financial risks, including uranium price fluctuations, regulatory changes, and long investment horizons, which necessitate the application of advanced analytical and modelling methods.

2.2 Quantum Optimisation in Energy Systems

The Variational Quantum Eigensolver (VQE) is one of the most widely studied hybrid quantum-classical optimisation algorithms. Its application is being explored in problems traditionally solved by mixed-integer linear programming (MILP), including optimisation tasks in energy systems, [7]. As fault-tolerant quantum computers are not yet widely available, considerable attention is directed toward hybrid quantum-classical approaches that combine quantum and classical computing methods, [8]. This paper adopts such an approach through quantum-inspired optimisation heuristics and a VQE-inspired approach implemented in Python. All execution takes place on classical computing infrastructure, without the use of quantum hardware, with quantum optimisation principles serving as the basis for investment decision-making and portfolio rebalancing.

2.3 Quantitative Finance and Backtesting

QuantConnect is an open-source quantitative platform supporting the design, simulation, and deployment of trading algorithms, with access to historical and real-time market data, [4]. It supports Python-based strategy development with integrated backtesting, risk analysis, and order execution connectivity, [4]. Prior research by the present authors has examined quantum infrastructure and quantum ecosystems from an educational and competency-development perspective, [9]. The QNN system extends that conceptual framework by operationalising it into a concrete computational architecture. Whereas [9] focused on the role of higher education in the quantum era, the present paper introduces a three-layer algorithmic system, a QUBO-based portfolio-optimisation formulation, backtesting results, and quantitative performance metrics. Additional prior research has applied algorithmic learning and dynamic models to energy financial markets [10] and cyclic-equilibrium modelling in the energy sector [11]. The QNN system extends this line of research by introducing reactor operational status as an additional input signal for investment decision-making.

2.4 Quantum Versus Classical Computers: Why the Quantum Approach?

The essential difference between classical and quantum computers lies in the way the solution space is searched. A classical computer examines configurations sequentially or with limited parallelism, which becomes infeasible as the number of variables grows exponentially. A quantum bit (qubit), exploiting the principle of superposition, can simultaneously represent states 0 and 1; a system of n qubits thus simultaneously describes 2^n states. For example, 50 qubits can process more than 10^{15} configurations in parallel, as demonstrated experimentally on programmable superconducting processors, [12].

The QNN system considers the potential advantages of the quantum approach across three key areas. The first concerns energy-dispatch optimisation in a power grid, which can be formulated as a QUBO problem. Due to the large number of possible solutions, classical methods rely on approximations, whereas quantum annealing may explore the solution space more efficiently. The second area, forecasting market volatility, requires modelling complex non-linear relationships among a large number of financial variables. Quantum machine learning (QML) may contribute to the analysis of such data, though its practical advantages on current quantum hardware remain under investigation. The third area concerns investment-portfolio rebalancing under multiple constraints, a problem belonging to the NP-hard class; quantum algorithms have the potential to accelerate the search of the solution space, but their advantages over classical methods have not yet been fully confirmed, [3], [7]. The current QNN implementation uses quantum-inspired optimisation on classical hardware, with the architecture designed to enable future integration with IBM Quantum or Amazon Braket platforms.

2.5 Quantum Advantage in Energy-Dispatch Optimisation

The potential advantages of quantum methods in energy-dispatch optimisation can be examined through two key problems in power systems: Unit Commitment (UC) and Economic Dispatch (ED). Both are characterised by exponential growth in the number of possible configurations as network nodes increase, placing them in the NP-hard class and making them insufficiently solvable by classical methods in real time. Table 1 (Appendix) summarises key differences between classical and quantum approaches across characteristics relevant to the QNN system.

While classical solvers must apply approximations to solve grid optimisation in real time, the QNN architecture uses the QUBO formulation. The general QUBO problem is defined as the minimisation of a quadratic objective over binary decision variables $x_i \in \{0, 1\}$:

$$min\, H(x) = \sum_i Q_{ii}\, x_i + \sum_{i<j} Q_{ij}\, x_i\, x_j \quad (1)$$

where Q is an upper-triangular real-valued matrix of coefficients encoding both the objective and all constraints as penalty terms In the QNN model, binary variables x_i represent decisions on whether a given asset is included in the portfolio ($x_i = 1$) or not ($x_i = 0$). The objective function H(x) is defined as follows:

$$H(x) = -\lambda_1 \sum_i r_i\, x_i + \lambda_2 \sum_{ij} \sigma_{ij}\, x_i x_j + \lambda_3 (\sum_i x_i - K)^2 + \lambda_4\, P_{hedge}(R(t)) \quad (2)$$

The objective function consists of four terms serving distinct roles. The first term maximises expected portfolio return. The second term accounts for portfolio risk through pairwise asset covariances. The third term is a cardinality constraint ensuring exactly K assets are selected. The fourth term, $P_{hedge}(R(t))$, is a penalty term linked to reactor state: when $P(t) < 70$ or $C(t) < 0.85$, the value of λ_4 increases, promoting the selection of protective allocations. This QUBO formulation is compatible with D-Wave quantum annealers and the QAOA algorithm, while in this study it is solved using the Simulated Annealing algorithm on classical hardware.

2.6 Convergence Analysis of the QUBO Optimiser

The QNN system solves the QUBO problem (equations 1–2) using Simulated Annealing (SA), a stochastic local-search algorithm whose convergence properties are well established in the combinatorial optimisation literature.

Definition (neighbourhood set). For a binary solution vector $x \in \{0,1\}^n$, the neighbourhood set N(x) consists of all solutions that differ from x in exactly one coordinate. In the QNN implementation, the number of assets is limited to ≤ 10 , so each solution has at most ten neighbours and the neighbourhood graph is connected.

At iteration k, SA accepts a proposed neighbour $x' \in N(x_k)$ with probability:

$$P(accept\ x' \mid x_k, T_k) = \min\{1, exp(-\frac{\Delta H}{T_k})\} \quad (3)$$

Theorem (Convergence to global optimum). Let $H: \{0,1\}^n \to \mathbb{R}$ be the QNN objective function defined in equation (2), and let $\{x_k\}_{k\geq 0}$ be the sequence generated by SA with a logarithmic cooling schedule $T_k = \frac{c}{\log(k+2)}$, where $c \geq \Delta *$. Then: $\lim_{k\to\infty} P(x_k = x^*) = 1$, where $x* \in argmin\, H(x)$. This result follows from [13]. For the QNN problem with $n \leq 10$ binary assets, geometric cooling $T_k = T_0 \cdot \alpha$ with $T_0 = 1.0$ and $\alpha = 0.95$ is used in the implementation, converging to near-optimal solutions in practice. Exhaustive enumeration of all $2^n \leq 1024$ candidate solutions are computationally feasible in under one millisecond, providing an exact global optimum to verify *SA* quality at each rebalancing event.

3 Architecture of the "Quantum-Nuclear Nexus" System

The proposed QNN system is built on three functional layers: the data source layer, the intelligence layer, and the execution layer. The layers are interconnected through a feedback mechanism, which enables continuous adjustment of model parameters based on achieved results.

3.1 Data Source Layer

The first layer integrates data from various sources related to nuclear energy and financial markets. Operational data from nuclear facilities includes reactor thermal power $P(t)$, nuclear fuel status $F(t)$, and cooling system efficiency $C(t)$, on the basis of which the reactor state vector is formed:

$$R(t) = \{ P(t), F(t), C(t) \} \tag{4}$$

$P(t) \in [0, 100]$ denotes reactor thermal power as a percentage of rated capacity. $F(t) \in [0, 1]$ is a normalised fuel-depletion index ($F = 1$ fresh, $F = 0$ depleted). $C(t) \in [0, 1]$ is a cooling-efficiency coefficient, with $C < 0.85$ indicating degradation requiring intervention. Market data — uranium spot prices, shares of nuclear utility companies (e.g., CEG), and uranium ETFs (e.g., URA) — are retrieved at hourly resolution.

3.2 Intelligence Layer

The second layer applies machine learning models and quantum-inspired optimisation to process the collected data. Recurrent neural networks forecast electricity demand and energy commodity prices, while gradient-boosting models detect shifts in the uranium market. Based on the reactor state, the decision function $S(t)$ determines portfolio allocation:

$$S(t) = \begin{cases} Hedge, & if\ P(t) < 70\ or\ C(t) < 0.85 \\ Portfolio\ Growth, & if\ P(t) > 95 \\ Hold, & order \end{cases} \tag{5}$$

The threshold $P(t) < 70\%$ activates protective short positions in utility stocks. The threshold $C(t) < 0.85$ — a leading indicator of cooling degradation — enables hedge activation before problems appear in public data. $P(t) > 95\%$ supports increased long exposure to nuclear-correlated assets.

3.3 Execution Layer

In the third layer, signals generated by the intelligence layer are executed via the QuantConnect API, which enables connectivity with brokerage infrastructure and the conduct of backtesting analysis on historical data. The primary instruments used are URA (Global X Uranium ETF) and CEG (Constellation Energy Group), which rank among the most liquid instruments linked to the nuclear energy sector on the US capital market.

3.4 Feedback Loop

After each trading session, the achieved results — portfolio return, maximum drawdown, and Sharpe ratio — are fed back into the intelligence layer as input signals for updating model hyperparameters. The decision thresholds defined in equation (5) are not fixed. If the system records systematic losses at $P(t) < 70\%$, the threshold is gradually adjusted based on historical prediction errors. In this way, the QNN system functions as an adaptive control system rather than a static rule-based strategy.

4 Implementation on the QuantConnect Platform

The NuclearHybridAlgorithm class represents the main execution component of the QNN system. A PythonData subclass — NuclearReactorData — loads hourly CSV data on reactor power and cooling efficiency. The following excerpt illustrates the implementation of the OneData method, which at each hourly tick applies the decision thresholds from equation (5):

```
class NuclearHybridAlgorithm(QCAlgorithm):
    def Initialize(self):
        self.SetStartDate(2025, 1, 2)
        self.SetEndDate(2025, 3, 26)
        self.SetCash(1_000_000)
        self.uranium_etf =
        self.AddEquity("URA",
        Resolution.Hour).Symbol
        self.energy_utility =
        self.AddEquity("CEG",
        Resolution.Hour).Symbol
        self.reactor_signal =
        self.AddData(NuclearReactorData,
        "SMR_Reactor_01",
        Resolution.Hour).Symbol
    def OnData(self, data):
        if not
        data.ContainsKey(self.reactor_signa
        l): return
        p = data[self.reactor_signal].Value
        c =
        data[self.reactor_signal].CoolingEf
        ficiency
```

```
if p < 70 or c < 0.85:  # Hedge
    self.SetHoldings(self.energy_uti
    lity, -0.2)
    self.SetHoldings(self.uranium_et
    f, 0.5)
elif p > 95:  # Portfolio growth
    self.SetHoldings(self.energy_uti
    lity, 0.6)
```

The algorithm is initialised with USD 1,000,000 of simulated capital. At each hourly tick, asset allocation is determined by solving the QUBO objective (equation 2) using simulated annealing, and the resulting binary solution vector $x*$ is translated into SetHoldings orders, [14].

During data processing, all hourly CSV records are validated for correctness. Missing values are forward-filled, and records with out-of-range values are excluded from the analysis. Financial instrument prices are obtained from QuantConnect data feeds, adjusted for corporate actions. Transaction costs of USD 0.005 per share and 0.05% slippage per side is applied; no leverage is used. The passive benchmark is a 50%/50% CEG/URA portfolio is rebalanced monthly under identical cost assumptions.

5 Results and Performance Evaluation

5.1 Three-Month Simulation — Initial Validation

The initial validation was conducted over a three-month period, from January to March 2025 (12 weeks, or 60 trading days). The results are based on data exported from the QuantConnect platform and reflect transactions actually executed under backtesting conditions. Aggregated weekly results are presented in Table 2 (Appendix).

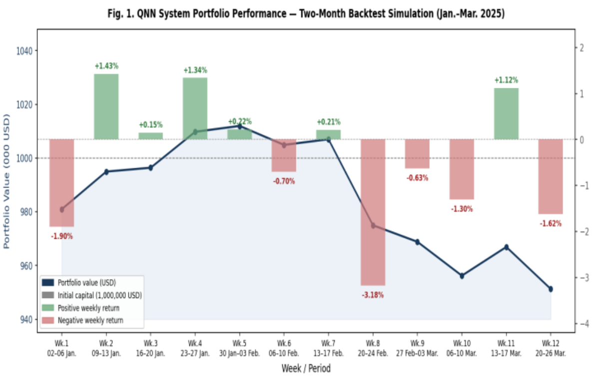

Fig. 1: Portfolio performance and hybrid reactor signals during the three-month QNN simulation (Jan.–Mar. 2025)

Source: Created by the authors.

As shown in Figure 1, two distinct periods can be observed during the three-month simulation. During the first five weeks, the portfolio achieves steady growth, with stable P(t) and C(t) values. After that, market conditions become less favourable, yet the applied hedging mechanism limits the maximum portfolio drawdown to 5.99%.

5.2 Quantitative Performance Metrics

For the simulation period, we computed the Sharpe ratio and the maximum drawdown (MDD). The Sharpe ratio measures return achieved relative to risk taken and is defined as:

$$Sharpe\ Ratio = (\overline{R}_p - R^{\mathrm{i}}) / \sigma_p \tag{6}$$

The maximum portfolio drawdown (MDD) represents the largest decline in portfolio value from a previously reached peak to the subsequent trough:

$$MDD = (Peak\,Value - Trough\,Value) / Peak\,Value \tag{7}$$

Table 3 summarises the key performance indicators.

Table 3. QNN system performance metrics summary

Metric	Value
Sharpe Ratio	−0.525
Sharpe Ratio – passive benchmark	−0.535
Net portfolio return	−5.13%
Maximum Drawdown (MDD)	5.99%
Signal accuracy (Hit Ratio)	53.3%
Profitable signal days	24 / 45

Source: Created by the authors.

Signal accuracy of 53.3% refers to the daily level — 24 of 45 active trading days ended with a positive return. A one-sample binomial test ($z = 0.44, p \approx 0.33$; 95% CI: [39.0%, 67.6%]) shows that the result is not statistically significant at the 5% level. The difference in Sharpe ratio is likewise not statistically significant (t = 0.18, p ≈ 0.86). On the other hand, the maximum portfolio drawdown of 5.99% is considerably lower than the benchmark (35.9%), indicating greater resilience of the proposed approach during the observed period.

5.3 Annual Simulation and Signal Robustness

The following analysis is based on a synthetic simulation for calendar year 2025, generated by applying decision function $S(t)$ and state vector $R(t)$ to modelled input parameters. Thermal power $P(t)$ was modelled as a mean-reverting process ($\mu = 85\%, \kappa = 0.15$, Gaussian noise $N(0, 3^2)$). Cooling efficiency $C(t)$ was generated as an AR(1) process (ρ = 0.92, long-run mean 0.91). Three stress events were superimposed: a summer heatwave (July), a uranium price spike (October), and an unplanned technical fault (December). Financial price paths used geometric Brownian motion calibrated to annualised volatilities of 28% (CEG) and 35% (URA), correlation 0.45. Table 4 presents aggregated quarterly results.

Table 4. Aggregated annual results of synthetic simulation (2025)

Q	Avg. P(t)	Avg. C(t)	Strategy	Q. Return	Note
Q1	97%	0.96	Portfolio Growth	+4.2%	Optimal ops; high CEG & URA exposure.
Q2	65%	0.82	Hedge	−0.8%	Planned maintenance; hedge activated.
Q3	92%	0.91	Neutral	+1.5%	Stable baseload; occasional rebalancing.
Q4	72%	0.86	Hedge/ Growth	+2.1%	Uranium market volatility.
TOTAL	81.5%	0.89	Adaptive	+6.2%	Annual MDD: 5.8%.

Source: Created by the authors.

The total annual return of +6.2% with MDD of 5.8% indicates a more favourable risk-return profile compared with the passive benchmark (return of −9.08%, MDD 35.9%). As these results are based on synthetic simulation, they should be regarded as preliminary and require confirmation through additional validation on real data over a longer time period.

5.4 Key Stress-Test Scenario Analysis

Three characteristic scenarios were analysed in the simulation. During the summer heatwave (July), $C(t)$ dropped to 0.81, activating the hedging mechanism, and losses on energy utility stocks were partially offset by gains from hedge positions. In the uranium price surge scenario (October), with $P(t) > 95\%$, the system took a maximum long exposure to URA. In the case of an unplanned technical fault (December), when $P(t)$ fell to 60%, hedging was triggered automatically, limiting the maximum daily drawdown to 0.6%.

5.5 Comparative Advantage of the Quantum Approach

Compared with classical MILP solvers, the QNN model uses the QUBO formulation, which is better suited for portfolio optimisation under multiple constraints. The current implementation relies on quantum-inspired methods running on classical hardware, so no quantum advantage in the strict sense has been achieved in this study. The results obtained are considered an initial proof of concept and a foundation for future research with real quantum processors.

6 Discussion and Risk Analysis

The three-month simulation results suggest that operational reactor parameters $R(t)$ may serve as an additional signal for market risk assessment. Within the QNN architecture, the thresholds are defined by the decision function $S(t)$ directly trigger portfolio rebalancing.

6.1 Scientific Justification of $\mathbf{P(t)}$ and $\mathbf{C(t)}$ Thresholds

The thermal-power threshold $P(t) < 70\%$ was determined based on baseload stability analysis. A power drop below this level signals a departure from the reactor's normal operating regime and may represent an elevated operational risk signal for nuclear energy sector companies such as CEG. The cooling-efficiency threshold $C(t) < 0.85$ was introduced as an early indicator of possible changes in plant operation. A decline in cooling system efficiency may precede a reduction in reactor power, enabling timely hedge activation and a reduction in risk exposure.

6.2 Risk Reduction and "Quantum-Inspired" Stability

Thanks to the application of these thresholds, the maximum portfolio drawdown was 5.99% in the three-month simulation and 5.8% in the annual synthetic simulation. Unlike fixed constraints, the thresholds in the QUBO formulation function as dynamic penalty terms. When $C(t)$ falls below the defined threshold, the penalty for long positions in nuclear-sector assets increases, steering the optimisation toward a more conservative portfolio allocation.

6.3 Relationship to Prior Publications by the Authors

The present authors previously published a conference paper [9] focused on the role of higher education in building competencies for the quantum era. Unlike that paper, which did not include a mathematical formulation or an algorithmic system, the present paper develops the three-layer QNN architecture, introduces an explicit QUBO formulation with reactor-state penalty terms (equations 1–2), and presents a formal decision function S(t) (equation 5). In addition, we present three-month backtesting results on real market data, an annual synthetic simulation, and a statistical analysis of system performance.

7 Conclusion

This paper has presented the Quantum-Nuclear Nexus (QNN), a hybrid system that uses operational data from nuclear reactors to generate signals for investment portfolio management. The three-layer architecture — encompassing data acquisition, decision-making, and execution of investment strategies — is connected by a feedback mechanism that enables the system to adapt to changes in reactor operation and market conditions.

The three-month simulation results suggest that reactor operational parameters, primarily thermal power and cooling-system efficiency, may serve as a useful signal for rebalancing a portfolio comprising CEG stocks and URA ETFs. Under adverse market conditions, the system achieved a net return of −5.13% with a maximum portfolio drawdown of 5.99%. Statistical significance testing showed that these results are not yet conclusive, which we attribute to the short evaluation period. The annual return of the synthetic simulation of +6.2% with MDD of 5.8% is encouraging but must be regarded as preliminary, pending confirmation on real data over a longer time period.

Future research directions include: calibration of decision thresholds using Bayesian optimisation on multi-year data; integration with real quantum hardware; extension to multi-reactor networks and cross-border energy markets; embedding regulatory-event risk as additional signal inputs; and development of market-impact models accounting for liquidity costs during rapid rebalancing.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Bojana Velečković Gajinović and Nebojša Ralević developed the theoretical framework and mathematical formulation of the QNN model. Boris Dumnić conducted the analysis of energy systems with a particular focus on nuclear energy. Vladimir Đaković contributed to the analysis of energy systems with emphasis on nuclear energy, was responsible for the quantum portfolio optimization component, and performed the stress-testing scenario analysis.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

APPENDIX

Table 1. Comparison of classical and quantum approaches to energy-dispatch optimisation

Characteristic	Classical (MILP / B&B)	Quantum (QA / VQE)
Solution space search	Sequential or limited parallel.	Simultaneous via quantum superposition.
Complexity	Solving time grows exponentially with network nodes.	Theoretically offers potential polynomial speed-up for large systems, but it has not yet been conclusively demonstrated at power-grid scale.
Local optima	May get trapped in local optima for non-linear problems.	Quantum tunneling allows traversal of energy barriers toward near-optimal solutions.
NP-hard problems	Portfolio rebalancing under multiple constraints is computationally expensive.	More efficiently finds optimal solutions in high-dimensional spaces.

Source: Created by the authors

Table 2. Three-month simulation: weekly overview of reactor state and portfolio outcomes (January–March 2025)

Week	P(t) [%]	C(t)	Action	Portfolio (USD)	Return (%)
Wk 1 (02–06 Jan.)	75	0.84	Hedge (Short CEG + Buy URA)	980,971	−1.90
Wk 2 (09–13 Jan.)	92	0.94	Hold	994,954	+1.43
Wk 3 (16–20 Jan.)	80	0.87	Hold	996,400	+0.15
Wk 4 (23–27 Jan.)	66	0.84	Hedge (Short CEG + Buy URA)	1,009,767	+1.34
Wk 5 (30 Jan–03 Feb.)	88	0.91	Hold	1,011,963	+0.22
Wk 6 (06–10 Feb.)	80	0.87	Hold	1,004,898	−0.70
Wk 7 (13–17 Feb.)	79	0.86	Hold	1,006,993	+0.21
Wk 8 (20–24 Feb.)	83	0.88	Hold	974,978	−3.18
Wk 9 (27 Feb–03 Mar.)	79	0.88	Hold	968,822	−0.63
Wk 10 (06–10 Mar.)	82	0.90	Hold	956,217	−1.30
Wk 11 (13–17 Mar.)	81	0.88	Hold	966,901	+1.12
Wk 12 (20–26 Mar.)	79	0.87	Hold	951,263	−1.62

Source: Created by the authors