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Research Article

Evolutionary Modeling and Analysis on Investment Consumption Optimization

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ABSTRACT
Genetic algorithms are optimization methods that are primarily used in financial analysis to facilitate better hands-on analysis with various software packages. The traders can use the parameters set, which are then applied using genetic algorithms for optimization. The financial applications optimize the parameters to represent the risks to the traders using evolutionary methods. Fixing the parameters is an essential step in the evolutionary process, and the financial parameters should correlate to modifications with market turns. This research focuses on determining the financial rank of supermarkets using clustering and evolutionary algorithms to identifythe risks in various decision-making and multi-disciplinary applications. This research also analyzes the optimal investment and some strategies required for consumption in asset modeling. The decision maker may fail in information processing due to the cost and can make financial portfolio decisions based on the signals observed. Hence this research developed the optimization model using clustering and evolutionary algorithms to determine the strength of observation, consumption strategies, and optimal investment based on the constraint value-at-risk and the cost of information processing. The wealth proportion spent by an investor on consumption lies between 0.01 and 0.09. Under the value-at-risk assumption, the stability of the optimal consumption proportion is inferred over the long-run period and will not exceed 7% of the investor's overall wealth.The experimental results prove that the proposed model works better than the state-of-the-art methods.

Keywords: financial risk, genetic algorithms, evolutionary algorithms, data clustering, investment optimization, investment consumption, value-at-risk, financial portfolio

1. INTRODUCTION

This research addresses the problem of investment consumption that the decision maker manages over the long-run perspective. For every investment, the typical financial data is the general observable. The decision maker should analyze the financial information based on availability. The fraction of every investment class should also be allocated dynamically to optimize the consumption utility over the long run [1-2]. Hence the financial objective should be considered for the investment problem and the consumption of assets. The global recession may also be possible because of liquidity and credit risks, and special attention is required to manage and measure the risks [3-4]. Rational inattention is used by decision-makers to process the constraints of information.

2. LITERATURE REVIEW

The selection methods of the financial portfolio are analyzed in the literature. Dynamic stochastic models are developed to study business cycles, signal observations, and variable filtering. Using constraints such as rational inattention, consumption and investment strategies are analyzed for economic factors observation [5-6]. The partial observable problem is also formulated based on the parameters and data processing cost [7-8]. The observable factor is evaluated by implementing the visual signal, state, and control variables subject to the constraint of value-at-risk. The decision maker controls the consumption in the framework, and the observation strength and consumption utility are maximized based on the requirement of value-at-risk.

The different models are proposed in the literature - examining the risk investments and dynamical state variables, achieving optimal strategies, modeling and approximating the dynamical systems using basis functions and linear equations, dynamic programming, partial differential methods, numerical methods, continuity and differentiability of dynamical systems, chains approximations and convergence [8-10].

Recently various soft computing strategies – machine learning (ML), logistic regression (LR), support vector machines (SVM), neural networks (NN), etc. have been applied to manage financial risks. These methods may result in a discontinuity in the solutions, and hence evolutionary algorithms are applied to improve the performance [4, 7, 9, 11-15].The issues in the probabilistic control problem are solved by proposing the evolutionary algorithm for optimal strategies that use the metaheuristics based on natural selection.

The research contributions are as follows:

- The value-at-risk constraint is considered for consumption and investment optimization.
- Applying the GA to avoid continuity and differentiability assumptions.
- Optimization of the wealth inflation dynamics formulation.

3. PROPOSED MODEL

The overall architecture of the proposed model is sketched in figure 1. The following notations and definitions are used in the proposed model [6-8, 12-13]:

3.1 Notations

F_t	financial filter information
t	observation time
μ	mean return rate
$C(t)$	investor consumption
$\pi(t)$	share of risk investment
$c(t)$	information cost
$u(t)$	control variable
r	risk-free return rate
$\alpha(t)$	control variable
$y(t)$	observable variable
$B(t)$	Brownian motion
$\beta(t)$	predicted coefficient estimation
$v(t)$	posterior variance
$dX(t)$	wealth process
$\Delta X(t)$	loss percentage
$var(t,\varphi,\hbar)$	value-at-risk at t
R	constant level

3.2 Definitions

$$u(t) = \big(\alpha(t), C(t), \pi(t)\big) \tag{1}$$

$$dy(t) = \sigma_y(t)dB_y(t) + (y - y(t).\lambda_y dt \tag{2}$$

$$\Delta X(t) = \exp(\hbar r) - X(t) - X(\hbar + t) \tag{3}$$

$$d\beta(t) = \big(\beta - \beta(t)\big)\lambda_\beta dt + \sigma_\beta dB(t) \tag{4}$$

$$var(t,\varphi,\hbar) = \inf\{0 \le L: L/Ft \le P(\Delta X_\emptyset(t) and\ L/Ft < \varphi \tag{5}$$

$$dX(t) = [X(t).r + X(t).\pi(t)(\beta(t) + \mu)(y(t) - y - r - ct - C(t)]dt + \sqrt{(V(t))}.\pi t X(t) dB1(t) \tag{6}$$

$$R \ge var(t,\varphi,\hbar) \tag{7}$$

The evolutionary model is defined in algorithm 1 as follows [8-14]:

Algorithm 1: Evolutionary model

1: Set the parameters of the genetic algorithm.
2: Initialize the population from the continuous uniform distribution.
3: Evaluate the population of individuals.
4: Perform the selection, crossover, and mutation of individuals to
- Minimize the risk of investment
- Maximize the return on investment
- Minimize the number of selected investment projects

5: Update the new population and continue the process until reachesa good approximation of equations (1) to (7).
6: Terminate the process and print the performance measures.

The main functions of the proposed model are as follows:

- Information preprocessing – apply the mining strategies to preprocess the required information.
- Financial Risk & Investment Consumption Optimization Analysis – apply the web mining, clustering, and the proposed evolutionary models to identify the risk and optimization.
- Clustering & GAs – Apply the sequential clustering and pruning strategies with the GA operators [5-9]. The financial analysis of the GA involves the cyclic operations:
  In-store monitoring ⇨ to readjust ⇨ build a new library ⇨ factor analysis ⇨ In-store monitoring
- Verification & validation – verify and validate the proposed simulated model by interacting with the online databases.
- Measures optimization – optimize the performance measures as defined in the

equations from (1) to (7) using approximation over the long run period of GA.

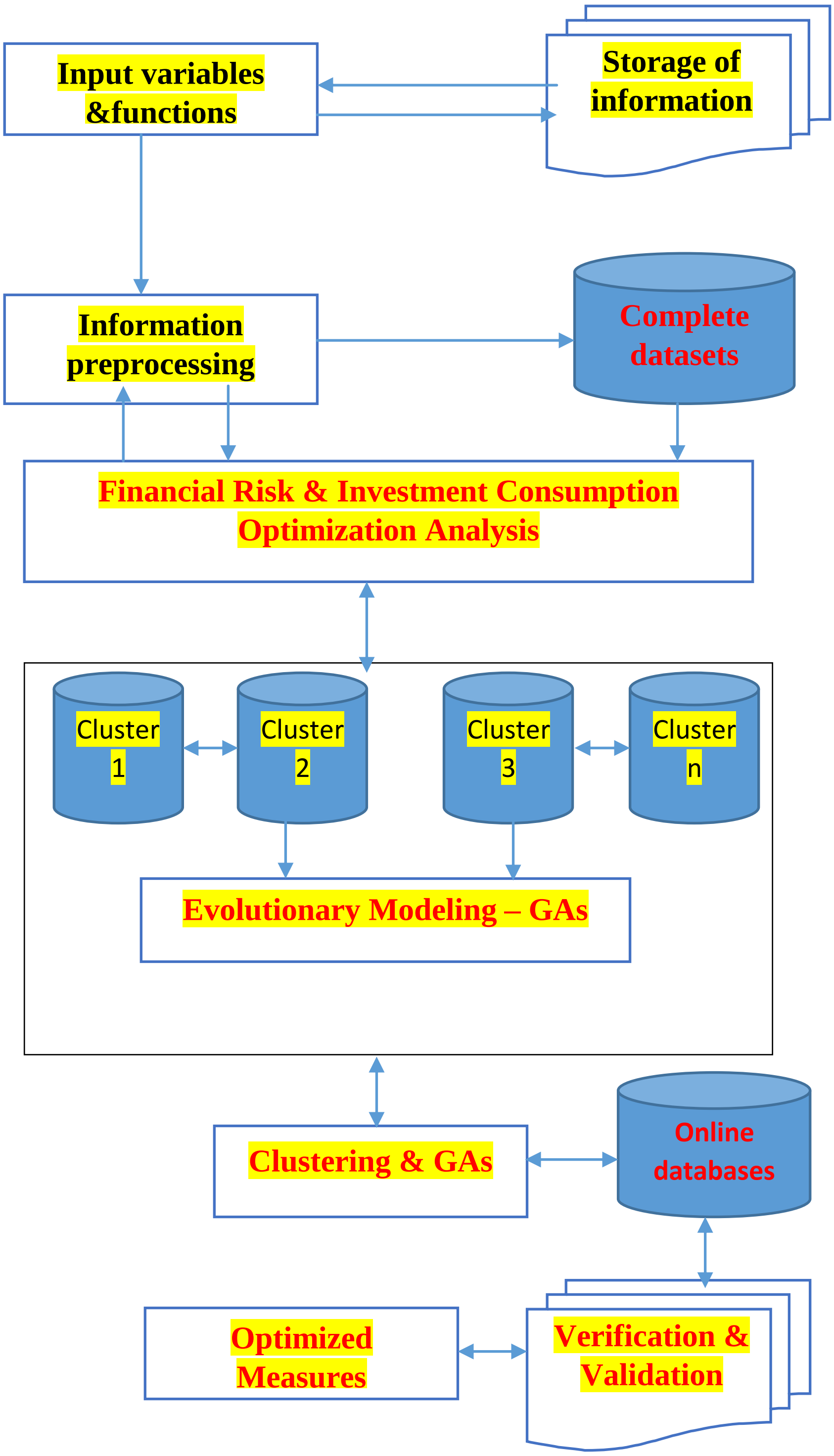

Figure 1: The architecture of the proposed model

4. RESULTS & ANALYSIS

The proposed model is simulated using the center of the online dataset, and the results are analyzed optimally for the proportion of asset allocation. The traditional methods of investment strategies are analyzed [9-13]. The data is collected from the center of the online dataset from January 2021 to June 2022.

The experimental outcomes conclude that the traditional methods limit the inefficient parametric search and are eliminated using the

GAs [7-12]. The expected return of the stocks for the 15 months is plotted in figure 2.

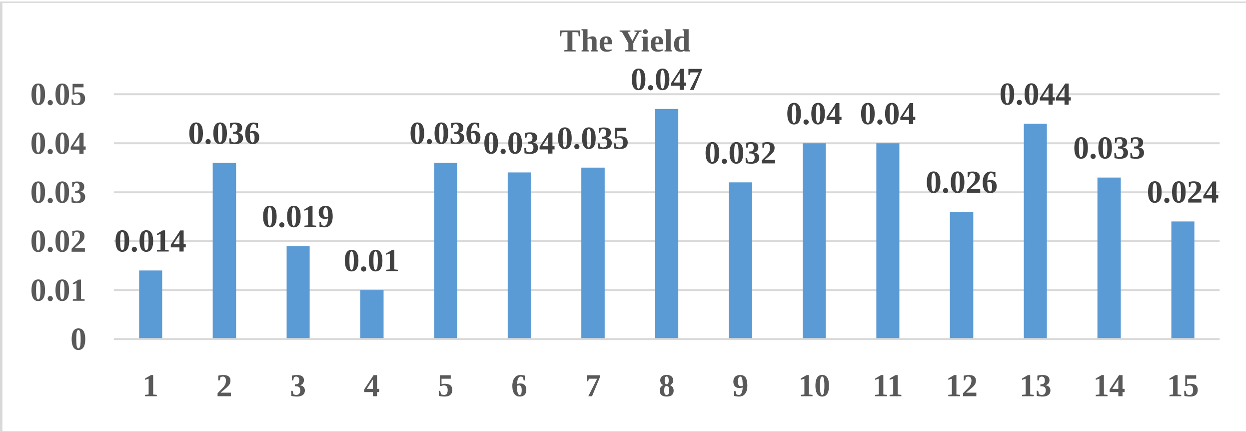

Fig.2: The expected return of the stocks

The performance of the GAs with the other iterative algorithms is depicted in figure 3. To analyze the financial portfolio the proposed model is tested on the stocks of different investment sectors. The simulation results conclude that compared to other models the GA results in a convergent solution that suggests buying 70% of entire assets will purchase one stock and the remaining 30% will purchase another stock in small-scale investments [5-6, 9-12]. The strategy of financial securities investment comparison with other models vs. GAs is sketched in figure 4.

The performance of the proposed model for years vs. wealth is sketched in figure 5. The years vs. optimal consumption is plotted in figure 6. Both of these figures conclude that the parameters of wealth and optimal consumption increase from the beginning to 60 years. For the given consumption as the utility function, the investor should increase the consumption. Too much consumption results in wealth down, implying that minimum wealth is expected to be spent in the future as a trade-off.

The simulation results also prove that when investors' wealth increases gradually, the consumption of trajectory results in some ups and downs. This is because sometimes the investor purchases significant tangible assets; in other situations, minimal spending is required for living expenses.

The wealth proportion spent by an investor on consumption lies between 0.01 and 0.09. Under the value-at-risk assumption, the stability of the optimal consumption proportion is inferred over the long-run period and will not exceed 7% of the investor's overall wealth.

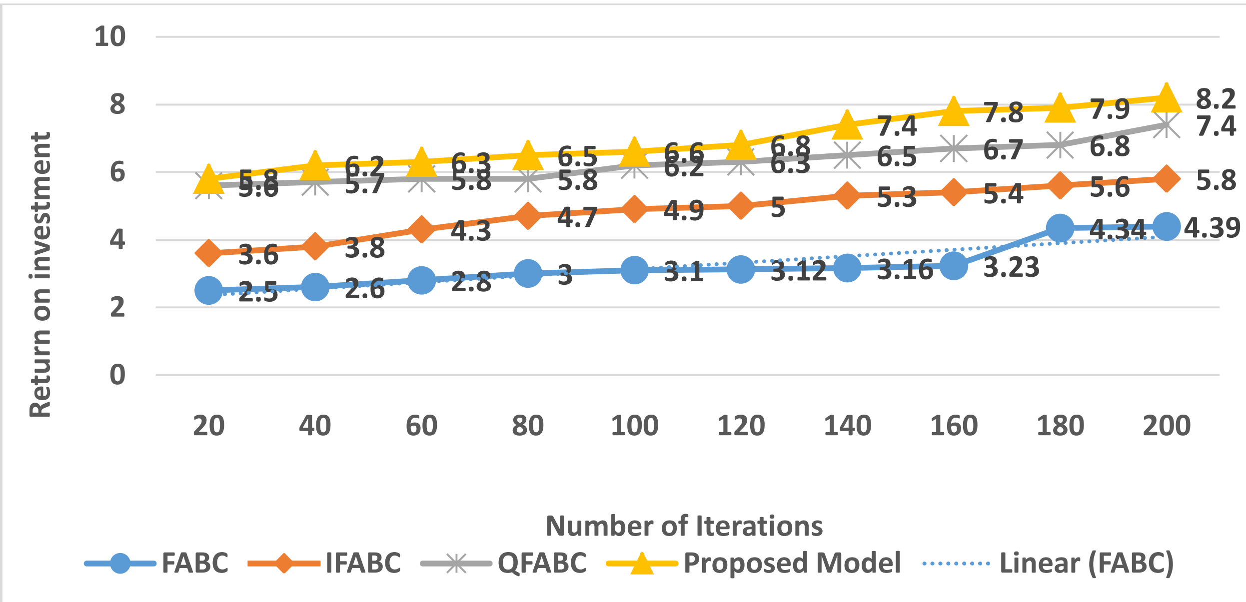

Fig.3: Performance of GAs with other iterative algorithms

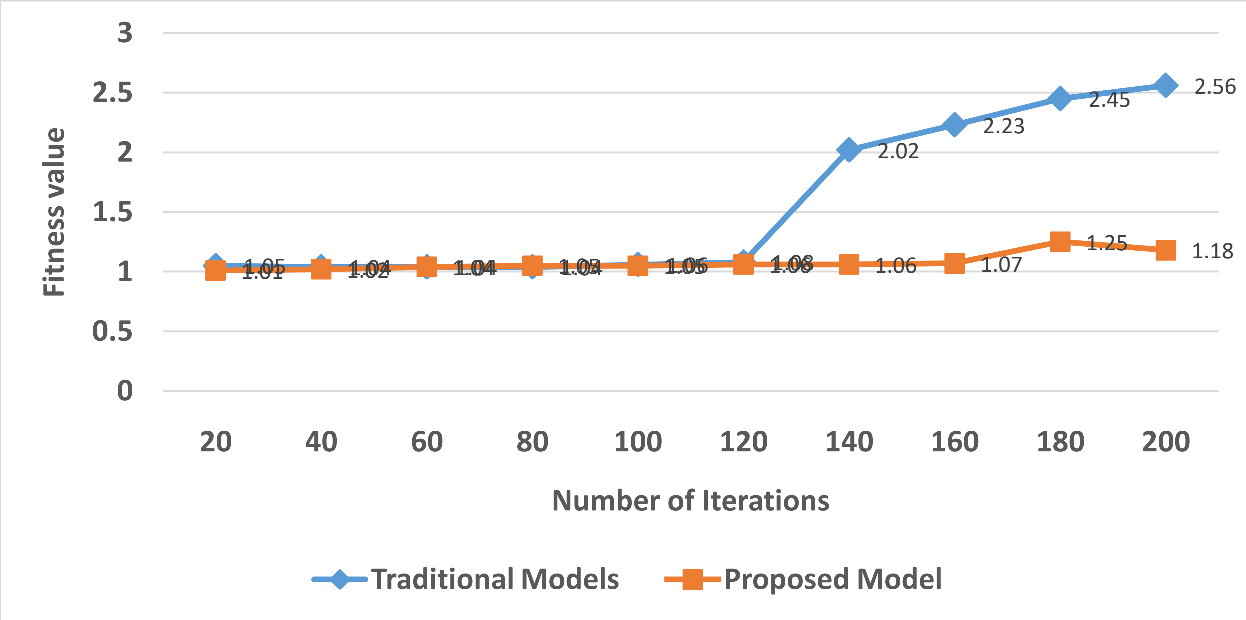

Fig.4: The strategy of financial securities investment comparison – other models vs. GAs

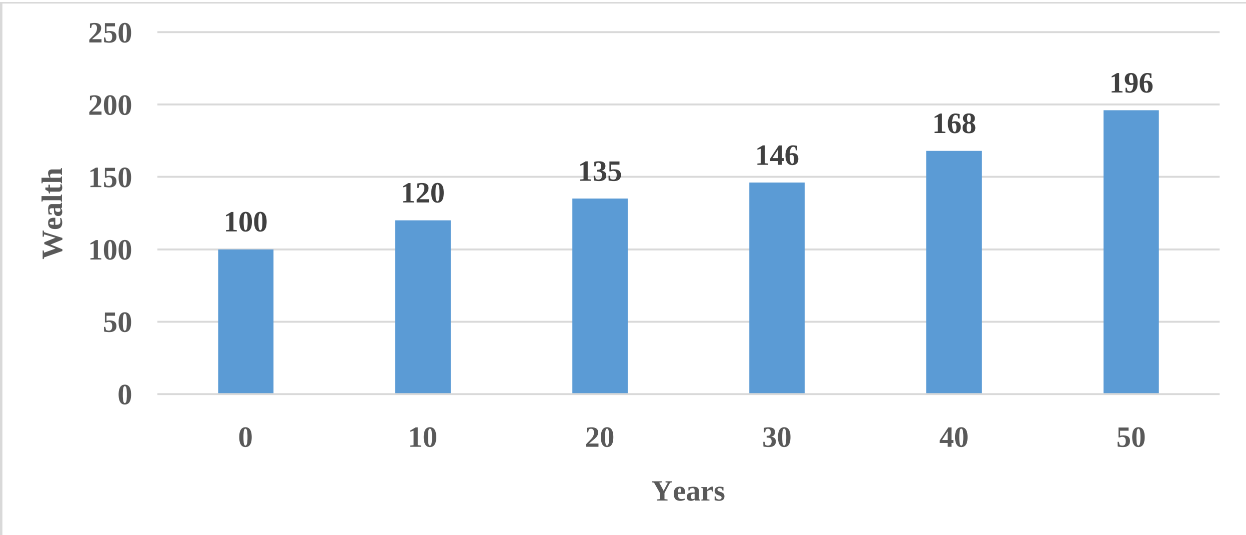

Fig.5: Years vs. wealth

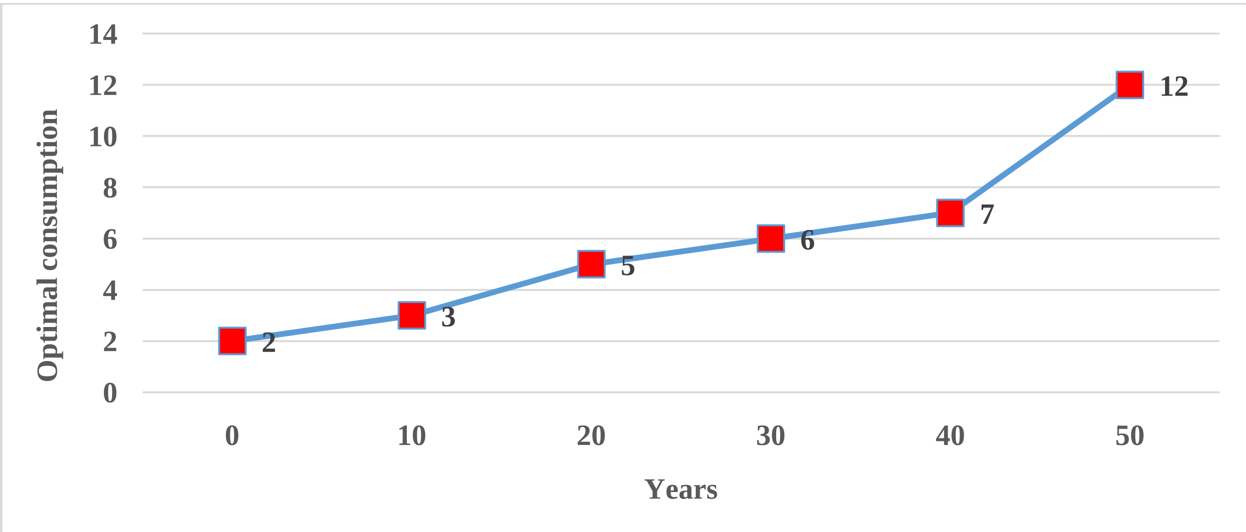

Fig.6: Years vs. optimal consumption

The following are the important results of the proposed model:

- Investment distribution is good compared to other models.
- The proposed model is also applicable for sparse problems that result in consistency.
- GA model is suitable for controlling the parameters globally.
- The investment in decentralization is also expected to achieve better measures.
- The problem complexity is reduced significantly for small and large-scale investment stocks.

5. CONCLUSIONS & FUTURE WORK

The new clustering and genetic algorithm model is developed to solve the financial portfolio problem. The research proposed a model based on value-at-risk constraints so that the decision-maker learns the strategies of optimal consumption and investment. Too much consumption results in wealth down, implying that minimum wealth is expected to be spent in the future as a trade-off. The simulation results also prove that when investors' wealth increases gradually, the consumption of trajectory results in some ups and downs. This is because sometimes the investor purchases significant tangible assets; in other situations, minimal spending is required for living expenses. The decision maker maximizes the objective function by filtering the economic factors since the return rate of assets is risky and partially observable. The wealth proportion spent by an investor on consumption lies between 0.01 and 0.09. Under the value-at-risk assumption, the stability of the optimal consumption proportion is inferred over the long-run period and will not exceed 7% of the investor's overall wealth.

The control variable identifies the cost and accuracy trade-off that determines the strength of the observation. The simulation results prove that the proposed representative works better than the state-of-the-art methods.

The following are the future work for this proposed model:

- The decision maker’s additional constraint, such as data processing, is to be considered.
- A new entropy measure is defined to quantify the capacity of data processing.
- New evolutionary and approximation algorithms will be developed to analyze the problem in the high dimensions [13-15].

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