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Article

Hybrid Modeling for Optimizing Vaccine Distribution in Remote Health Stations

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ABSTRACT
This study aims to enhance the Expanded Programme on Immunization (EPI) vaccine distribution to distant Barangay Health Stations by testing a hybrid Genetic Algorithm (GA)-Particle Swarm Optimization (PSO) model. Incorporating GA's exploratory route generation and PSO's convergence guidance, the approach revealed a more efficient route, lowering delivery cost and allowing timely and reliable vaccine delivery. It simulated a hybrid Genetic Algorithm–Particle Swarm Optimization (GA–PSO) model for route planning in order to optimize the efficiency of delivery routes. GA explored new delivery routes through crossover and mutation, while PSO refined solutions toward optimal paths. The hybrid GA-PSO combined broad exploration with fast convergence, avoiding premature settling and uncovering hidden efficiencies, ultimately producing smarter, more reliable vaccine distribution strategies for remote health stations. In this study, both GA and PSO individually identified NP → NM → K with a cost of 25. The hybrid GA-PSO revealed a smarter shortcut, NP → SD → K, lowering the cost to 22. This hybrid approach achieved cheaper, faster, and more reliable vaccine distribution compared to single algorithms. It demonstrates the first application of a hybrid GA-PSO model to vaccine cold-chain logistics in remote health stations. Balancing GA's creativity with PSO's convergence prevents premature settling, uncovers hidden efficiencies, and offers a practical optimization framework for real-world public health supply chains.

Keywords: EPI vaccine distribution hybrid modeling, vaccine distribution in remote health stations, EPI vaccine route optimization, hybrid GA–PSO distribution modeling, public health supply chains

1. Introduction

The "cold chain" is time-critical, complex, and dynamic (Yakobi et al., 2025; Yin et al.,2022; Ko et al., 2015). It is an integrated system of equipment (e.g., cold rooms, shipping containers, refrigerators, vehicles), procedures, records, and activities used to handle, store, transport, distribute, and monitor temperature-sensitive products (Olufadewa et al., 2019; Phelan, 2022; Lou, 2016; Shen et al., 2022), and very common in perishable good like dairy (Iyer et al., 2025; Carson et al., 2017; Wu et al., 2021; Kocaoglu et al., 2020), processed/fresh food (Bruzonne et al., 2014; Daofang et al., 2015; Wari et al., 2015), poultry and all agricultural products (Kartoglu et al., 2014), and vaccines (Carson et al., 2017; Lemmens et al., 2016) where shelf life is directly affected by temperature conditions. Vaccines used in the "Expanded Programme Immunizations (EPI)" are distinct from other products in the chemical and pharmaceutical industry (Chen et al., 2024). Unlike conventional commodities, vaccines prevent and avert untimely death or a lifetime of disability from a variety of infectious diseases (Weil, 2016; Orenstein et al., 2017; Haakenstad et al., 2016). The success of EPI, therefore, hinges on the capability of supply and logistics systems. Maintaining this integrity to obtain, stock, and convey vaccines at appropriate temperatures and deliver them promptly, and in the right condition (Weil, 2016; Jalloh et al., 2020; Taylor et al., 2014; Chan, 2014).

The EPI was propelled by the World Health Organization (WHO) way back in 1974. Its motivation was basic and direct which is to deliver various vaccines to all children through a basic timetable of child visits to the barangay health stations (BHS) (Hillan et al., 2024; Steinglass, 2013; Chan, 2014) established through routine immunization (RI) across nations that gives admittance to life sparing immunizations, control and destroy vaccine-preventable diseases (Bhattacharjee et al., 2014; Shen et al., 2014; Masemola et al., 2025). It will likely guarantee that immunization administrations are available, accessible, worthy, and reasonable to clients in a productive and powerful way (Bhattacharjee et al., 2014; Kumar et al., 2022). Moreover, it is recognized as one of the most successful public health interventions ever devised (Anderson et al., 2014; Xiao-tao et al., 2016; Lemmens et al., 2016).

The vaccine cold chain is an important component of immunization programs, as it keeps vaccines safe from manufacturing to distribution to the child. It is kept in storage at medical facilities until it is needed for immunization. There are different schemes used for immunization, one of which is outreach delivery, where vaccines are carried to a remote site for use or people come to the facility for immunization (Summan et al., 2025; Jiang et al., 2024). It must be handled carefully at every stage of the cold chain to guarantee its maximum effectiveness. These include storage and transport of vaccines from the rural health unit (RHU) to the end user and further down at the outreach sites, commonly at BHS (He, 2024; Lemmens et al., 2016). Due to its temperature sensitivity, the mode of transportation, and the time during distribution, issues arise. In Panabo City, the RHU (City Health Office) is serving forty (40) BHS.Several BHS are geographically distant. The vaccines used for EPI are carefully packed and placed in a bucket with ice packs by the cold chain manager. These vaccines are claimed at the RHU and carried by the assigned staff from the BHS. Given this scenario, planning a mode of transportation is necessary. In the rural area, the usual mode of transportation is a tri-wheeled vehicle (e.g., Tuk-Tuk, Tricycle) or a two-wheeled vehicle (motorcycle) to the geographically distant barangay. Considering the road and weather conditions, and one-way restrictions due to road construction or rehabilitation. These factors impact the maintenance of the potency of the vaccines to keep them in a safe temperature range, which, in turn, if not given attention, may result in instability of vaccines and inadequacy of supply in the immunization schedules (Hu et al., 2022; Yin, 2025). Furthermore, ever since the EPI was launched back in 1974, no one has really taken a deep look at how vaccine demand is spread across different communities. This means we still lack a clear picture of how people's need for vaccines has shifted and grown over time. Thus, determining and optimizing the direct dispersal route is an essential component of the EPI vaccine distribution to ensure a stable supply, lessen delivery costs, and improve delivery performance.

In the study of (Sharma et al., 2012), the integration of Dijkstra's shortest path algorithm with the Genetic Algorithm was presented as a fast and scalable re-routing algorithm that adapts to dynamically changing networks. "Dijkstra's algorithm (DA)" is used to define the antecedent array, which helps with the genetic algorithm's commencement step. Then the "genetic algorithm (GA)" keeps finding the best routes with appropriate genetic operators under dynamic traffic situations (Celebi, 2015; Sharma et al., 2012). The results of the experiment show that DGA provides routes that result in a lesser extent of travel time and computationally estimates the briefest route between "source and destination" overhead than pure "genetic algorithm-based techniques in large-scale routing issues".

In reference (Karole et al., 2025), a node for static and dynamic routing networks was applied by combining DA and GA to find the shortest path. The results confirmed that both algorithms offer the same result, demonstrating the power of the genetic algorithm. The execution time of both algorithms was compared, and it was discovered that DA takes longer to determine the optimal path than GA. So, GA has the potential to replace DA in finding the shortest path for network topologies (Tiwari et al.,2020).

In recent years, GA has been utilized for security implementation for undisclosed information and transferring the data commissioning "confidentiality through cryptography, verification, veracity, and non-repudiation of messages". A key pair is generated using an algorithm that has been created and implemented. To create an intermediate cipher, a plaintext is encrypted using the private key (PK). The intermediate cipher is encrypted again using a genetic process to create the final cipher (He et al., 2013; Roghanian et al., 2014; Lee et al., 2012).

Scientific decision-making was predicated on accurate forecasting of area logistics demand. Two weight value determination approaches, the Arithmetic Means Method and the Validity Method, were compared after analyzing "Trend Extrapolation, the Grey System Method, and the Regression Method". Then, the notion of utilizing GA to enhance weight values was proposed. The predicted outcomes of turnover volume of freight transport in region A showed that the GA can minimize the sum of squared errors (Najafi et al., 2015). A solution based on GA is developed for the effective management of the distribution network of a Turkish automotive manufacturer under centralized control and reverse logistic network under a stochastic environment (Wang et al., 2015). In the study of (Mageswari, 2024), a multi-objective integrated logistic model is proposed to locate disaster relief centers while considering network costs and responsiveness. Because this location problem is NP-hard, a genetic method for solving the proposed model is described.

Moreover, GA is utilized in optimization problems for the food process industry (Yun et al., 2020; Diabat et al., 2016). Optimization is gaining popularity as a decision-making technique, particularly considering the current surge in optimization difficulty issues, including those of sophistication and computational complexity. It is regarded as one of the most applicable tools for complex optimization problems among other techniques. Moreover, it is widely used in processing technologies, which include fermentation, dehydration, thermal excrescence, and extraction, as well as in optimizing transportation, stowage, scheduling, and planning production-related activities. Optimizing single-objective drawbacks is considered an issue, while multi-objective optimization problems are becoming increasingly popular. Further, the utilization of hybrid GA-based exploration in the management of the integrated supply chain in a company is an imperative element of every administrative process as it gears towards augmenting performance. A multi-echelon joint location-inventory model is developed in the study of (Herwanto et al., 2024; Xu et al., 2024; Wu, 2017). Hence, GA is a useful tool for solving distribution problems, but it faces several limitations when applied to large and complex systems. In big networks such as supply chains, GA often converges slowly, taking a long time to identify good solutions because it explores too many possible routes instead of narrowing down quickly (Zhang et al., 2025).

It also has the characteristic of premature convergence, that is, the algorithm will converge to "good enough" delivery schedules and will lose schedules that are better than the ones it has found, because of the loss of diversity in the population (Alexakis et al., 2025). The other challenge is that the computational complexity is very slow and expensive if it is run with 1000 nodes, vehicles, or constraints (Satif et al., 2025). It is also very sensitive to parameters such as mutation rate, crossover rate, population size, etc. – setting a few parameters incorrectly can result in sub-optimal results. Last but not least, GA is not necessarily an ideal option.

In distribution problems, the PSO can be more suitable than GA due to its rapid convergence, avoidance of common pitfalls, and adaptability to dynamic conditions, as indicated by the work of Chen et al., (2024) and Yao et al., (2024). However, GA tends to be too general. Like explorers that scan all the ways to deliver the goods, PSO has the behavior of flocking birds that follow the leader quickly to reach food; it can converge faster in large-scale supply chains (Zhang et al., 2024; Zhao et al., 2024). On the other hand, GA can get complacent with the "good enough" schedules and exploit the same ones, while PSO also explores and exploits by dynamically adjusting the velocity of the particles, maintaining the curiosity of the "flock" to navigate new routes (Bade et al., 2024). In the resources part, GA needs to check a lot of people over generations, while PSO does not require as many particles and simpler updates to carry out, hence lighter computationally. Unlike PSO, which uses primarily the inertia weight and acceleration coefficients, which are more easily adjustable, GA is sensitive to parameter tuning (Garg et al., 2024). PSO is more flexible in the face of changing logistics scenarios, including variations in traffic or demand, as particles continually evolve in response to the latest optimal solutions (Mcnulty et al., 2024). GA and PSO are both applied to distribution optimization, but in different ways. In simple terms, GA is well suited to static, complex problems with the need for deep searching, and PSO is well suited to dynamic, real-time problems such as making on-the-fly delivery route changes.

Hybrid models for distribution optimization have been designed and developed to take advantage of the best of both approaches by having GA complement PSO's weaknesses and vice versa. The GA–PSO enables the explorers to continue to search broadly and the flock to converge more quickly into good solutions. The hybrid approach is more likely to work in more complex and dynamic distribution systems, as was the case with vaccine delivery in remote regions, where in-depth planning coupled with rapid adaptation is essential. That is, GA and PSO work better together as presented in Table 1.

Table 1. Comparison of optimization algorithms.

Aspect	Genetic Algorithm (GA)	Particle Swarm Optimization (PSO)	Hybrid GA–PSO
Convergence Speed	Slower, thorough exploration.	Faster, quick convergence.	Balanced: GA explores widely, PSO speeds up convergence.
Premature Convergence	Risk of settling too early.	Maintains diversity better.	Hybrid reduces risk by combining GA's diversity with PSO's guidance.
Computational Cost	Heavy, resource-intensive.	Lighter, simpler updates.	Moderate: more efficient than GA alone, but heavier than PSO.
Parameter Sensitivity	Needs careful tuning of mutation/crossover.	More forgiving with fewer parameters.	Hybrid smooths sensitivity by blending GA's flexibility with PSO's simplicity.
Adaptability	Less flexible in dynamic conditions.	Highly adaptive to changes.	Strong adaptability: GA explores new routes, PSO adjusts quickly.
Best Fit	Static, complex problems.	Dynamic, real-time challenges.	Large, complex, and changing logistics systems (e.g., vaccine distribution).

2. Methods

2.1 Network Connecting Remote Barangay Health Stations

The EPI vaccines are initially transported to the Provincial Health Unit (PHU), where they are stored in a designated cold storage room to maintain their integrity. From there, these vaccines will be distributed to the Rural Health Unit (RHU), which also maintains a cold storage facility. In Panabo City, the cold chain operations are carefully overseen by the cold chain manager, ensuring that the vaccines are handled properly and stored at the correct temperature levels.

This study focuses on the geographically distant (GD) barangays' health stations (BHS) of Panabo City, which serve as key points for vaccine delivery. The most used vehicles available for transporting to these areas are the tri-wheeled vehicle (tricycle or tuk-tuk) and the two-wheeled vehicle (motorcycle).

Figure 1 presents a simplified view of the road network connecting GD BHS, showing real-time traffic cost data. Each node, labeled 1,2,3,4,5,6, represents a GD BHS. These nodes represent the crossroads network. The numbers marked along each route indicate the cost. The cost is computed by dividing the distance from the road by the real-time driving speed, considering delays during the waiting time for the available vehicle, and the road condition. This helps assess the efficiency of vaccine delivery routes and identify potential bottlenecks.

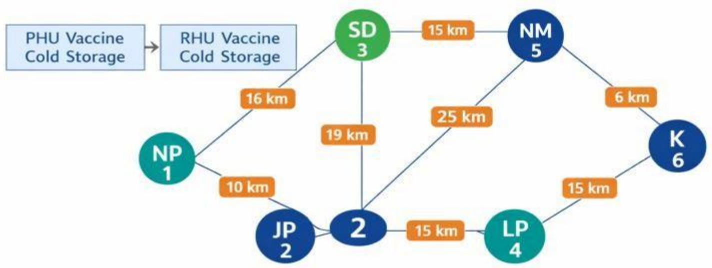

Figure1. Simple View of the Road Network connecting GD BHS.

2.2 Process Flow of the Hybrid GA-PSO

The first step in distribution optimization using a hybrid GA/PSO is to define the problem and to create potential solutions. Every solution is evaluated for a target, which can be loss reduction or efficiency. To maintain diversity of solutions and to explore new possibilities, the genetic algorithm (GA) steps of selection, crossover, and mutation are used. Particle

The Swarm Optimization (PSO) algorithm then comes into play, which further optimizes those solutions by directing the particles to the best-known solutions, thus accelerating convergence. GA does this by switching between these two approaches, so that the search is not prematurely stuck on an unpromising solution, but searches the space of interesting options further. This cycle is repeated until the algorithm stabilizes to an optimal, balanced solution that simultaneously uses GA's wide exploration and PSO's focused exploitation to achieve an efficient distribution plan, as shown in Figure 2.

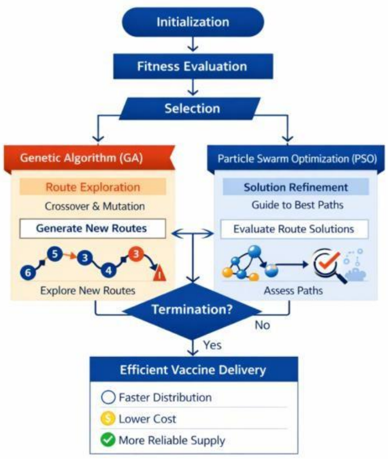

Figure 2. Process Flow of the Hybrid Model of GA and PSO for Distribution Optimization.

The hybrid GA-PSO algorithm is similar to a cycle, which contains the characteristics of both algorithms. It begins with an initialization process where random routes and particles are generated to investigate potential solutions. Then there is a fitness function which determines the quality of each route with respect to the objective, say minimizing cost or distance. GA operators (selection, cross-over, mutation) modify these routes and maintain diversity by mixing and slightly mutating them. Then the PSO update is used to update the position and velocity of the particles with the use of their own previous best (pBest) and the global best (gBest), which directs the search process to the promising areas. GA's new individuals have their exploration combined with PSO's update in the hybridization stage, which makes exploration faster and more convergent. Last but not least, the algorithm performs a test for its termination: once the best solution is obtained or the maximum number of iterations is met, the algorithm terminates; otherwise, it goes back to the fitness evaluation to continue improving until the optimal path is obtained.

2.3 *Hybrid GA-PSO Algorithm*

The hybrid GA–PSO algorithm works like a cycle that mixes the strengths of both methods. It is further illustrated in the following steps.

Step 1: Initialization
- 2.3.1 Generate an initial population of candidate solutions.
- 2.3.2 Assign random positions and velocities to particles (PSO)
- 2.3.3 Encode solutions as chromosomes (GA).

Step 2: Fitness Evaluation
- 2.3.4 Evaluate each candidate using the distribution objective function (cost, delivery time, load balance).

Step 3: Selection
- 2.3.5 Select top-performing individuals to generate offspring.
- 2.3.6 Use techniques like single-point or uniform crossover.

Step 4: Crossover (GA)

2.3.7 Apply crossover to selected individuals to generate offspring.

2.3.8 Use techniques like single-point, two-point, or uniform crossover.

Step 5: Mutation (GA)

2.3.9 Apply mutation to offspring to maintain genetic diversity.

2.3.10 Use random bit flips or Gaussian perturbations.

Step 6: PSO Update (For each particle)

2.3.11 Update velocity:

$$v_i^{t+1} = w \cdot v_i^t + c_1 \cdot r_1 \cdot \left(pBest_i - x_i^t\right) + c_2 \cdot r_2 \cdot \left(gBest - x_i^t\right) \quad (1)$$

2.3.12 Update position:

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (2)$$

Table 2. Key Parameters

Parameter	Description
Population size	Number of candidate solutions
w	Inertia weight (PSO)
c1, c2	Cognitive and social coefficients
r1, r2	Random numbers between 0 and 1
pBest, gBest	Personal and global best positions
Mutation rate	Probability of mutation (GA)

Step 7: Hybridization

2.3.13 Replace a portion of the GA population with updated PSO particles.

2.3.14 Use PSO's global best to guide GA offspring toward optimal regions.

Step 8: Termination Check

2.3.15 If stopping criteria are met (e.g., max iterations or convergence threshold), terminate.

2.3.16 Else, return to Step 2.

3. Results

The simulations are performed using the hybrid GA–PSO in this section. For each optimization method, there is a corresponding Genetic Algorithm (GA), which acts as a sort of personality, exploring the surroundings with an adventurous spirit, but eventually finding a solution. The Particle Swarm Optimization (PSO), on the other a solver, the focused problem hand, rapidly gathers around promising tracks. The hybrid GA–PSO combines both properties – exploring sufficiently to avoid blind spots, and refining solutions becomes easier to optimize – not only efficiently with numbers. With this context, the simulation results appreciate, showing how different better outcomes like me to condition strategies "think" their way toward.

3.2 Routes Generated from NP to K

3.2.1 NP → NM → K; Cost = 19 + 6 = 25

3.2.2 NP → SD → NM → K; Cost = 16 + 15 + 6 = 37

3.2.3 NP → SD → JP → LP → K; Cost = 16 + 25 + 15 + 15 = 71

3.2.4 NP → JP → LP → K; Cost = 10 + 15 + 15 = 40

The simulation shows that the efficiency of various routes from NP to K varies. The shortest path is NP→NM→K and the least expensive is NP→NM with a cost of 25. On the other hand, the longest is NP → SD reflecting the additional JP → LP→K with the steps and complexity of the above being 71. There is a middle NM →K in between these. However, the choices made for (37) and ground, such as NP → SD → K (40), the shortest path NP → JP → LP are not the same match speed and coverage. This comparison illustrates that although it reduces the amount of resources consumed, it may not reach as many checkpoints as intermediate routes, and the longest route (which is the most expensive) may reach the most checkpoints. It is a compromise between efficiency and completeness.

3.3 Simulation

Step 1: Initialization

- GA population: Randomly select routes (chromosomes).
- PSO particles: Each particle represents a route with position (sequence) and velocity (possible swaps).

Step 2: Fitness Evaluation

- Fitness = inverse of cost (lower cost → higher fitness). Example: Fitness(route) = 1 / cost.
  - NP → NM → K → Fitness = 1/25 = 0.04
  - NP → SD → NM → K → Fitness = 1/37 ≈ 0.027
  - NP → JP → LP → K → Fitness = 1/40 = 0.025
  - NP → SD → JP → LP → K → Fitness = 1/71 ≈ 0.014 Step 3: GA Selection
- Select top routes: NP → NM → K and NP → SD → NM → K. Step 4: GA Crossover

- Combine routes:
  - Parent1: NP → NM → K
  - Parent2: NP → SD → NM → K
  - Offspring: NP → SD → K (new candidate, cost = 16 + 6 = 22). Step 5: GA Mutation
- Randomly alter offspring: NP → JP → K (invalid since JP doesn't connect directly to K, discarded).
- Valid mutation: NP → LP → K (cost = 19 + 15 = 34 if NP → NM → LP → K is allowed).

Step 6: PSO Update

- Each particle adjusts toward:
  - pBest: its best route so far.
  - gBest: global best route (currently NP → NM → K, cost = 25).
- Example: NP → SD → NM → K particle shifts toward NP → NM → K by reducing detours.

Step 7: Hybridization

- GA offspring NP → SD → K (cost = 22) replaces weaker PSO particles.
- PSO guides GA toward NP → NM → K. Step 8: Termination
- After several iterations, the algorithm converges to NP → SD → K (cost = 22) or NP→ NM → K (cost = 25), depending on mutation/crossover balance.
- Final optimal route: NP → SD → K with cost 22 (discovered via hybridization).

The comparisons of the three approaches illustrate the different ways they search. The pure Genetic Algorithm (GA) was investigated extensively and was ultimately chosen to go through the sequence–NP → NM → K (25). A pure Particle Swarm Optimization (PSO) was able to find a solution in a shorter period because it used the same path; however, there is a tendency to have zero solutions. The hybrid GA – PSO in the quick promising part is interesting, → K (22). This found an even better path: NP → SD shows the strength of combining GA's diverse options' ability to explore for refining solutions quickly. Together with PSO's knack, they balance exploration and exploitation, leading to smarter results than either, more efficient method alone, as presented in Table 1.

4. Discussion

The proponent examined various delivery paths in the simulation, each of which had a cost associated with it, which is equal to the distance or effort required to deliver it. The Genetic Algorithm (GA) was like a creative problem-solver - it 'bred' new routes by mixing and mutating existing ones. The Particle Swarm Optimization (PSO) was more like a flock of birds, where each route learned from its own best path, as well as the group's best path. Initially, both methods were more inclined towards NP → NM → K with a cost of 25 and appeared to be the most straightforward. When GA and PSO are integrated, however, GA found a new solution, NP → SD → K, that is even cheaper, with a cost of 22. Then PSO assisted in fine-tuning this discovery by steering particles into the stronger options. What GA does is give people the imagination to think in different directions; what PSO does is give them the discipline to come together and converge quickly, and together they are responsible for finding a smarter, cheaper route.

5. Conclusion

Hence, a hybridized method of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) produces a better method to distribute optimization. GA's function was like the explorer who was testing and mixing new routes to find new possibilities, and PSO's function was like the flock, which was able to rapidly steer solutions towards the known path. When used independently, both approaches converged on NP → NM → K (25), but in their combination, it was found that the new path NP → SD → K (22) is better. The result demonstrates that the combination of the broad search of GA and the convergence speed of PSO helps avoid premature convergence and find shortcuts that may not be obvious. Hence, GA provided the creativity to explore, PSO added the discipline to converge, and their teamwork led to a smarter and cheaper solution. This illustrates the real-world applicability of hybrid GA-PSO in logistics, particularly for logistics tasks that demand efficiency, such as distributing vaccines.

Author Contributions

Conceptualization, M.R.; methodology, M.R.; validation, M.R.; formal analysis, M.R.; resources, M.R.; data curation, M.R.; writing-original draft preparation, M.R.; writing-review and editing, M.R.; visualization, M.R.; project administration, M.R. The author has read and agreed to the published version of the manuscript.

Data Availability Statement

Data are available from the corresponding author upon request.

Conflict of Interest Statement

The authors declare that they have no financial, personal, or professional conflicts of interest related to this manuscript.

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