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# An Effective Taguchi Design For Parameter Tuning in Ant Colony Optimization Applied to the Capacitated Hub Location Problem

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## ABSTRACT

The parameter setting is a critical and computationally challenging issue for the successful implementation of the ant colony optimization (ACO) algorithm. This study proposes an efficient experimental design method using the Taguchi method for parameter optimization of ACO applied to the capacitated hub location problem. Four key parameters including the ant colony size, evaporation rate, selective preferences, and stopping condition are designated as design factors. The total transportation cost is adopted as the performance characteristic, while the number of potential hub nodes, the number of hubs, and the number of customers served are considered noise factors to simulate diverse problem environments. A robust design experiment utilizing inner and outer orthogonal arrays is conducted via computer simulation to determine the optimal parameter setting. The validity of this optimal setting is then confirmed by comparing its signal-to-noise ratios with those obtained from a full factorial design experiment.

**Keywords**: Ant colony optimization, Parameter optimization, Taguchi method, Hub location problem

## INTRODUCTION

The application of heuristic search methods to solve combinatorial optimization problems has recently attracted much attention. Since Dorigo and Stützle [1] developed the basics of ant colony optimization (ACO), this metaheuristic has proven efficient for numerous complicated problems. However, the identification of appropriate parameter settings remains the most critical and time-intensive issue for the successful implementation of ACO, making it one of the most active subjects of current research. A number of approaches have been suggested to derive robust parameter settings for search algorithms. In one of the most extensive studies, Schaffer et al. [2] concluded that optimal parameter settings vary significantly from problem to problem. Other systematic approaches include a decision support system proposed by Pakath and Zaveri [3] for determining appropriate parameter values, and an experimental design approach using full factorial design discussed by Gupta et al. [4]. Furthermore, Hsieh et al. [5] successfully used the Taguchi method to find optimal operating parameters in genetic algorithms to improve efficiency. More recently, Leung and Wang [6] and Liu et al. [7] demonstrated the utility of the Taguchi method in seeking optimal breeding to efficiently generate the iterative solutions and establish algorithm with higher performance.

In this study, we propose a new and efficient experimental design method for parameter optimization in an ACO for the capacitated hub location problem (CHLP) using the Taguchi method. Robust designs such as the Taguchi method utilize principles from statistical design of experiments to evaluate and implement improvements. Its fundamental principle is to improve the quality of the characteristic of interest by minimizing the effect of variation causes, rather than eliminating the causes themselves. To achieve this, four commonly studied ACO parameters are treated as design factors: the ant colony size, the evaporation rate, the selective preferences, and the stopping condition defined as the number of consecutive iterations without improvement. The total transportation cost is adopted as the performance characteristic. The number of potential nodes, the number of hubs, and the number of customers to be served are considered noise factors to generate various problem environments. An experimental design is constructed using inner and outer orthogonal arrays for the design and noise factors, respectively. At each factor combination, the performance

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characteristic is obtained, and the signal-to-noise (SN) ratio is calculated as a robust measure. These SN ratios are analyzed using the analysis of variance (ANOVA) technique to determine the optimal settings of the design factors that are robust to noise factors. The validity of the optimal parameter setting is investigated by comparing its resultant SN ratios with those obtained from a full factorial design experiment.

The remainder of this paper is organized as follows. Section 2 reviews Taguchi's philosophy for performance improvement. Section 3 describes the CHLP and presents the specific ACO developed for this study. Section 4 presents the design of the orthogonal array experiment and the analysis of the experimental data. Finally, conclusions are drawn in section 5.

## Taguchi Method

This section presents the basic concept of the Taguchi method. The performance of a process, typically measured by specific characteristics, varies due to a variety of causes. These causes are collectively referred to as noise factors. The fundamental principle of robust design (or parameter design) as proposed by Taguchi, is to identify the optimal settings of design factors that minimize the influence of noise factors on the performance characteristics [8]. To achieve this, Taguchi advocates for an experimental approach utilizing orthogonal arrays. This methodology allows for the efficient determination of a large number of design factors with a minimal number of experimental runs. Furthermore, the effect of noise factors on the performance characteristic is captured by the signal-to-noise (SN) ratio.

### Overview and Experimental Strategy

For robust design, Taguchi suggests an experiment where orthogonal arrays are employed to systematically arrange both the design and noise factors. Specifically, the design factors are assigned to the inner array and the noise factors are assigned to the outer array. The noise factors are kept separate from the design factors. They are arranged to form different testing conditions. This separation enables the measurement of the performance characteristic's sensitivity to noise factors, which is then quantified by an appropriate SN ratio. Identifying the important noise factors is a critical step in parameter design and typically requires engineering experience and judgment. Figure 1 illustrates a typical experimental plan for parameter design.

| | Inner array | Outer array | |
|---|---|---|---|
| | design<br>factors<br>D1 D2 D3 | 1 2 2 1<br>1 2 1 2<br>1 1 2 2 | N3<br>N2 noise<br>N1 factors |
| 1<br>2<br>3<br>4 | 1 1 1<br>1 2 2<br>2 1 2<br>2 2 1 | Experimental<br>Data<br>$y_{ij}$ | SN Ratios<br>$SN_i$ |

Fig. 1. Experimental strategy for parameter design

### Loss Functions and SN Ratios

Taguchi classifies performance characteristic into three categories, i.e., the-smaller-the-better (SB), the-larger-the-better (LB), and a-specific-target-best (TB). For example, total cost is an SB characteristic, while throughput is an LB characteristic. Taguchi suggests that performance be quantified by the loss incurred due to the deviation of the performance characteristic from its target value. Given that the exact functional form of this loss may be complex or unknown, a quadratic loss function is recommended. For a TB performance characteristic, $y$, with a target value, $t$, the quadratic loss function is defined as $L(y) = k(y-t)^2$. Similarly, the quadratic loss functions for the SB and LB cases are given by $L(y) = ky^2, L(y) = k/y^2$ ,respectively. The expected loss is composed of two elements: one related to the deviation of the mean $\bar{y}$ from the target value and the other related to the variance of $y$ caused by noise factors. The ultimate objective of robust design is to find the design factor settings that minimize the expected quadratic loss. This objective is mathematically equivalent to

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maximize the SN ratio. Different SN ratios are employed based on the specific nature of the performance characteristic $y$.

## CHLP Model and ACO Algorithm

### Problem Description of the CHLP Model

The problem under study is computationally challenging to solve exactly, especially as the size of the problem instances increases. Therefore, we propose a hierarchical solution framework based on two efficient steps to obtain near optimal solutions for the CHLP within a reasonable computational time. For the application of this hierarchical approach, it is convenient to distinguish between two types of decision. The first refers to the hub selection, that is, the optimal number of hubs are selected among a given set of candidate hub locations. The second decision refers to the allocation of customers, that is, each customer node is allocated to a selected hub. The proposed algorithm is applied to these two sub-problems hierarchically [9, 10].

### Selection of Hub Locations

The ACO algorithm is one of the most well-known search techniques based on swarm intelligence. ACO based algorithms have been widely applied to combinatorial optimization problems and have demonstrated distinguished results [11]. During the search process, the number of hubs to be used must be determined at the beginning of each iteration. Let $p$ denote the number of hubs used by the colony, which is chosen as a random number. The solution for the hub selection can then be constructed using the following probabilistic equations.

$$k = \begin{cases} \arg\max\limits_{k \in L_h^s} \left( \tau_k^s \left( \eta_k \right)^{\alpha} \right), & \text{if } q \le q_0 \\ K, & \text{otherwise} \end{cases} \tag{1}$$

$$K : P_k^h = \frac{\tau_k^s \left( \eta_k \right)^{\alpha}}{\sum\limits_{k \in L_h^s} \tau_k^s \left( \eta_k \right)^{\alpha}} \tag{2}$$

Here, $L_h^s$ is the set of candidate hub locations not yet selected by ant $h$ in the $s$th iteration, and $\tau_k^s$ is the amount of pheromone on each candidate hub $k$ in the $s$th iteration. The parameter $\alpha$ establishes the importance of heuristic information compared to the pheromone quantity in the selection process. The value $q$ is a random uniform variable in [0, 1], and $q_0$ is a parameter. If $q \le q_0$, the ant selects the node with the highest value from equation 1. Otherwise, the ant selects a random variable $K$ to be the next hub using the probability distribution defined in equation 2. The heuristic information $\eta_k$ must be defined considering various problem specific characteristics. In this paper, we consider the capacities of candidate hubs, traveling costs, and fixed hub costs as follows.

$$\eta_k = \frac{\pi_k}{\sum\limits_{i \in C} \sum\limits_{j \ne i \in C} w_{ij} \left( \chi c_{ik} + \delta c_{kj} \right) + \sum\limits_{l \in W_h^s} \gamma c_{lk} + f_k} \tag{3}$$

where $W_h^s$ is the set of hub locations selected by ant $h$ in the $s$th iteration. Intuitively, a candidate hub node with large capacity, low fixed cost, and incurring low traveling cost is likely to be selected as a hub.

### Allocation of Customers to Hubs

After the hub selection phase is completed, each customer node is successively allocated to a hub by the following probabilistic formula,

$$r = \begin{cases} \arg\max_{r \in W_h^s} \left( \xi_{ir}^s \left( \psi_{ir} \right)^{\beta} \right), & \text{if } q \le q_0 \\ R, & \text{otherwise} \end{cases} \tag{4}$$

$$R : P_r^h = \frac{\xi_{ir}^s \left( \psi_{ir} \right)^{\beta}}{\sum_{r \in W_h^s} \xi_{ir}^s \left( \psi_{ir} \right)^{\beta}} \tag{5}$$

In these equations, $i$ is the index of the current customer node to be assigned to a hub and $r$ is the index of any potential hub. A flow potential vector $\boldsymbol{W}$ is computed, where the $i$th component, $W_i$, represents the sum of the flows from node $i$ to all other nodes. Nodes are sorted in decreasing order of flow potentials, and at each construction step, an ant $h$ selects the next, still unassigned, customer node $i$ as a candidate for allocation. Additionally, $\psi_{ir}$ is defined by equation 6. Intuitively, the heuristic information should prefer a hub that has low transportation cost with the candidate node and low capacity requirements.

$$\psi_{ir} = \begin{cases} \dfrac{\pi_r}{c_{ir} \sum_{j \ne i \in C} \left( w_{ij} + w_{ji} \right)}, & \text{if the capacity of hub } r \text{ is not violated} \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

If the solution violates the hub capacity constraint, it is disregarded for the remainder of the iteration, and the ant is considered as a dead ant. This construction process continues until all customer nodes are allocated to a hub.

**Pheromone Updating Rule**

After the ants select the hubs, the amount of pheromone on these selected hub nodes decreases due to natural evaporation. The amount of pheromone on each allocated customer-hub pairs also decreases. The local pheromone updating rule in the proposed ACO can be defined as follows.

$$\tau_k^s = \rho \tau_k^s + \left(1 - \rho\right) \tau_0, \quad \forall k \in W_h^s \tag{7}$$

$$\xi_{ir}^s = \rho' \xi_{ir}^s + \left(1 - \rho'\right) \xi_0, \quad \forall ir \in B_h^s \tag{8}$$

Here, $\rho, \rho'$ are control parameters for the evaporation speed. $\tau_0, \xi_0$ are the initial pheromone values assigned to all potential hub nodes and the arcs representing all customer-hub pairs in the network, respectively. In this paper, $\tau_0, \xi_0$ are set to the inverse of initial total costs found for a particular problem instance. $B_h^s$ is denoted as the set of customer-hub pairs selected by ant $h$ in the $s$th iteration.

After a predetermined number of $w$ ants generate feasible solutions, global pheromone updating is conducted. This is achieved by adding pheromone to each of the hub nodes and allocated customer-hub pairs contained in the current best solution found at that iteration. The global pheromone updating rule can be described as follows.

$$\tau_k^s = \rho \tau_k^s + \left(1 - \rho\right) \Delta \tau_k^s, \quad \forall k \in T_{bs} \tag{9}$$

$$\xi_{ir}^s = \rho' \xi_{ir}^s + \left(1 - \rho'\right) \Delta \xi_{ir}^s, \quad \forall ir \in T_{bs} \tag{10}$$

where $\Delta \tau_k^s = \Delta \xi_{ir}^s = 1/L_{best}$, which is the reciprocal of the value of the current best solution, $T_{bs}$. Before global pheromone updating is performed, a local search is applied to improve the quality of the current best solution found in each iteration.

## Experimental Design and Analysis

### Design Factors and Their Levels

The performance of a developed ACO algorithm is highly dependent on its specific parameters. In this study, we selected four of the most commonly investigated ACO parameters as design factors: the ant colony size, stopping condition that implies the number of consecutive iterations without improvement, the evaporation rate, and the selective preferences. Following an extensive preliminary analysis of the algorithm, three levels were chosen for each parameter value. The selected design factors and their corresponding levels are summarized in Table 1.

Table 1. Design factors and their levels

| level / factor | 1 | 2 | 3 |
|---|---|---|---|
| (1) ant colony size ($A$) | 50 | 100 | 150 |
| (2) stopping condition ($B$) | 30 | 40 | 50 |
| (3) evaporation rate ($C$) | 0.05 | 0.075 | 0.1 |
| (4) selective preferences ($D$) | 0.8 | 1.0 | 1.2 |

### Noise Factors and Their Levels

To minimize the sensitivity of the performance characteristic to noise factors, it is crucial to estimate this sensitivity consistently across all combinations of the design factor levels. While various noise factors exist within CHLP environments, engineering judgment must be used to decide which factors are more important and what testis testing conditions are appropriate to effectively capture their effects. In this study, three noise factors were selected, while others were judged to be less significant and were consequently ignored. The selected noise factors and their corresponding levels are listed in Table 2.

Table 2. Noise factors and their levels

| level factor | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| (1) number of potential nodes ($U$) | 5 | 10 | 15 | 20 |
| (2) number of hubs ($V$) | 2 | 3 | 5 | |
| (3) number of customers ($W$) | 50 | 100 | 150 | |

Although the noise factors in this study are evaluated through systematically generated computer simulations to model diverse operational environments, they are designed to closely mirror the structural characteristics found in real-world logistics networks. Specifically, the ranges for the number of potential nodes, hubs, and customer configurations are reflective of regional hub-and-spoke transportation environments, such as those adapted in standard benchmark instances (e.g., the AP and CAB datasets). This alignment ensures that the robust parameter settings derived herein maintain practical relevance for real-world logistical planning.

### Experimental Design

The experimental design was set up to estimate the main effects of the four design factors as well as the two-way interactions $AB$, $AC$ and $BC$. The interactions between the ant colony size ($A$) and the stopping condition ($B$) were specifically anticipated based on experience. Interactions between the ant colony size ($A$) and the evaporation rate ($C$), and between the stopping condition ($B$) and the evaporation rate ($C$) were also of particular interest.

An orthogonal array was chosen as an efficient method for simultaneously studying the effects of these multiple design factors. For the inner array, the orthogonal array $L_{27}(3^{13})$ ,which features 13 three-level columns and 27 rows, was selected. The design factors *A*, *B*, *C*, and *D* were assigned to columns 1, 2, 5, and 9, respectively. The testing conditions were determined using an outer array containing 12 combinations of the noise factors. Factors *U*, *V*, and *W* were respectively assigned to columns 1, 2, and 3 of the outer array. Each row of the inner array $L_{27}$ represents a unique process design, and the performance (total transportation cost) of each design was evaluated via computer experiment under every noise condition specified by the outer array.

**Data Analysis**

The primary purpose of conducting this matrix experiment was to determine the level of each factor that yields the highest SN ratio. For the present problem, the SN ratio at each row of the inner array was calculated as follows. Since the ideal value of the total transportation cost is zero, the corresponding SN ratio is given by

$$\eta = -10\log(\frac{1}{12}\sum_{j=1}^{12} y_j^2), \tag{11}$$

where $y_j$ is the normalized deviation of the observed total cost at test condition *j* from the minimum value of that specific condition *j*. Maximizing $\eta$ directly leads to the minimization of the quality loss. After the SN ratios were calculated, the next step in data analysis involved evaluating the significance of each effect's effect on the characteristic. Based upon the analysis of variance (ANOVA), the optimum levels of the statistically significant design factors at the 0.05 level and their contribution ratios are presented in Table 3.

Table 3. Optimum levels and contribution ratios based on $\eta$

| factor | Optimal level (contribution ratio) |
|---|---|
| *A* | $A_2$ (8.48 %) |
| *B* | $B_3$ (25.04 %) |
| *C* | |
| *D* | $D_1$ (9.25 %) |
| *AB* | $A_2B_3$ (32.13 %) |
| *AC* | |
| *BC* | |

From table 3, the optimum settings of the design factors for $\eta$ were initially determined as $A_2B_3D_1$. Factor *C* (evaporation rate) was found to have no statistically significant effect on the total transportation cost. Consequently, the optimum level of *C* was determined by selecting the level that maximized the $\eta$ value, which was $C_3$. Although a verification experiment conducted using the full factorial design showed that the setting $A_3B_3C_2D_1$ yielded the highest $\eta$, the $\eta$ value obtained at the setting $A_2B_3C_3D_1$ was very close to the maximum. Based on these findings, we conclude that the optimum design $A_2B_3C_3D_1$ represents a good compromising solution. It should be noted that this optimal setting was obtained with a far smaller experiment ($L_{27} \times L_{12}$) compared to the full factorial design ($L_{81} \times L_{12}$). It is worth noting the distinct methodological advantage of the proposed Taguchi-based parameter tuning framework over alternative optimization methods, such as standard full factorial designs, genetic algorithms (GA), or particle swarm optimization (PSO). Conventional metaheuristic tuning approaches often demand prohibitive computational overhead due to expansive iterative searches across the parameter space. In contrast, the orthogonal design employed in this study drastically minimizes experimental resource requirements by evaluating the parameters using only 324 runs ($L_{27} \times L_{12}$). This represents a significant reduction in computational cost while successfully yielding a compromising solution ($A_2B_3C_3D_1$) that remains robust against external noise factors.

## CONCLUSIONS

In this study, we presented a novel and efficient experimental design method for parameter optimization in an ACO algorithm applied to the CHLP utilizing the Taguchi method. Four specific parameters were treated as design factors: the ant colony size, the evaporation rate, the selective preferences, and the stopping condition. The number of potential nodes, the number of hubs, and the number of customers to be served were considered as noise factors for generating various problem environments. A robust design experiment, employing inner and outer orthogonal arrays, was conducted via computer simulation. This process yielded the optimal parameter setting, which consists of a specific combination of the level for each design factor. The validity of the optimal parameter setting was thoroughly investigated by comparing its SN ratios with those obtained from an experiment utilizing full factorial designs.

Nevertheless, this study acknowledges certain limitations regarding the inherent properties of the Taguchi method. While our inner array experiment systematically investigated primary two-way interaction effects (such as AB, AC, and BC), standard orthogonal configurations may partially oversimplify highly complex, non-linear, or dynamic relationships that naturally occur between ACO parameters during extended execution. To overcome this limitation and further expand the comprehensiveness of the optimization process, integrating advanced dynamic experimental designs, machine learning-driven hyperparameter tuning, or Bayesian optimization remains an important avenue for future work.

Furthermore, while this study establishes a robust foundational framework using simulation-based experiments, a promising direction for future research involves validating the proposed Taguchi-based ACO approach against large-scale, empirical datasets from actual industry logistics and public transportation systems to further enhance its practical applicability.

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