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Single Row Facility Layout Problem using Fuzzy Larsen Simulated Annealing

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Abstract— **The Single Row Facility Layout Problem (SRFLP) is considered an NP hard problem, involving the search for an optimal arrangement of rectangular facilities with equal height and varying lengths. This paper introduces a novel approach that uses fuzzy logic system with Larsen Inference system to adapt the simulated annealing algorithm main parameters. The proposed algorithm is tested against the classical simulated annealing algorithm on SRFLP benchmark problems.**

Keywords— Simulated annealing, Fuzzy logic system, parameter control , Single-Row Facility Layout Problem, Larsen inference system

I. INTRODUCTION

The Single-Row Facility Layout Problem (SRFLP) objective is to find the optimal arrangement of rectangular facility, with predefined lengths and traffic intensities between each two facilities while minimizing the overall cost associated with inter-departmental flow. SRFLP is applicable in different fields, such as arranging machines in manufacturing [1], and organizing rooms in hospitals [2]. The Single-Row Facility Layout Problem (SRFLP) is characterized by the following definition:
Consider a set F = {1, 2, ..., n}, comprising n > 2 rectangular facilities with a fixed height and varying lengths li > 0, for each i in F. Additionally, let cij = cji ⩾ 0, for i, j in F, represent the weight between facilities i and j, typically denoting a transmission cost between them. A specific solution to the SRFLP involves an ordering π = { π (1), π (2), ..., π (n)} of the facilities in F, where the cost C(π) is determined by the objective function outlined as follows:

$$C(\pi) = \sum_{1 \le q < r \le n} C_{\pi(q)\pi(r)} . d_{\pi(q)\pi(r)} \quad (1)$$

where dπ(q)π(r) is the distance between the centers of facilities π(q) and π(r).
The distance is computed by:

$$d_{\pi(q)\pi(r)} = \frac{l_{\pi(q)}}{2} + \sum_{q<s<r} l_{\pi(s)} + \frac{l_{\pi(r)}}{2} \quad (2)$$

The goal of the optimization problem is to find the best π⋆ that minimizes the function C(π).

$$\pi^* = \arg\min_{\pi \in \Pi n} C(\pi) \quad (3)$$

where Πn represents the set of permutations of the first n positive integers.

Many metaheuristics were used to solve SRLP such as hybrid simulated annealing [9], ant colony algorithm [10], scatter search [11], particle swarm optimization [12], tabu search [13], artificial immune system [14] and multi-start simulated annealing [15].

This paper employs fuzzy logic with Larsen controller to adapt the parameters of the simulated annealing (SA) algorithm to solve the SRFLP. We name this algorithm Fuzzy Larsen Simulated Annealing (FLSA). The parameter’s update is done based on the state of the optimization progress. Section 2 presents the work related to our research. In Section 3, we describe our proposed approach. Section 4 details the experimental methodology

The final section offers conclusions on the research outcomes presented in this paper.

II. RELATED WORK

In this study, our primary focus is on the adaptation of Simulated Annealing (SA). Numerous studies have employed fuzzy logic to dynamically control various parameters of SA. For instance, in [20], the Mamdani inference method within fuzzy logic is employed to regulate the cooling speed of the SA algorithm. Another instance is found in [8], where a Mamdani fuzzy logic controller is utilized to adapt SA's neighborhood structure. Additionally, in [6], fuzzy logic is applied to dynamically adjust the current temperature and acceptance probability of SA. In a related work [19], a Type-2 fuzzy logic system is employed to control the same parameters as in the preceding study.

Beyond SA, other metaheuristics have been improved through the integration of fuzzy logic. Notable examples include the control of population size for Ant Colony System (ACS) in [17], modulation of local pheromone in [15], and adaptation of pheromone parameters in [18][21]. Furthermore, alternative approaches such as the use of Hidden Markov Model (HMM) have been explored. In [22], HMM is employed to govern SA parameters [29] [30], specifically adapting the cooling schedule of the SA temperature. This method is extended to adapt the neighborhood structure in [24]. Moreover, HMM is leveraged to dynamically control parameters in other algorithms such as ACS, where pheromone parameters, evaporation parameter, and pheromone level exponent are automatically adjusted [16] [25]-[28].

To our knowledge, the control of all SA parameters using fuzzy logic has not been explored. In our contribution, we introduce FLSA, a self-adaptive algorithm utilizing fuzzy logic with the Larsen inference system. This novel approach dynamically adjusts the temperature, acceptance probability, and local search operator of SA to effectively address the Single Row Facility Layout Problem (SRFLP).

III. SA PARAMETER CONTROL USING FUZZY LOGIC

A. Simulated Annealing

Simulated Annealing (SA) draws inspiration from the annealing process in metallurgy and was introduced by Kirkpatrick et al. in 1983 [3]. This algorithm discovers optimal solutions for optimization problems by dynamically balancing exploration and exploitation, mirroring the annealing process. The initial phase involves a high temperature, promoting the exploration of non-optimal solutions. As the temperature decreases, the algorithm transitions to a phase that emphasizes preserving areas containing good solutions.

The Generalized Simulated Annealing [4] is distinguished by two parameters: qv, denoting the visiting parameter, and qa, referred to as the acceptance parameter. When qv/2 = qa = -1, the algorithm embodies fast simulated annealing, while qv = qa = 1 configures the algorithm to behave as a classical simulated annealing. The characteristics of the algorithm, including the cooling schedule, the probability of acceptance, and the neighborhood structure, are mathematically formulated through equations that explicitly incorporate the qv and qA parameters. These parameters play a crucial role in tailoring the behavior of the algorithm, allowing for a spectrum of annealing strategies ranging from rapid exploration to the more traditional simulated annealing approach

Since we are working on a problem of combinatorial optimization, we will focus in this paper, on the temperature and the acceptance probability functions of the GSA, so we replace qv with qT in the temperature function and we call this variable the temperature parameter.

The GSA function of temperature is as follows:

$$T_{qT}(t) = T_0 \frac{2^{qT-1} - 1}{(1+t)^{qT-1} - 1} \quad (4)$$

The acceptance probability formula that we will be using in our work is the generalized Metropolis algorithm mentioned in [6] and defined as:

$$p_{qa} = \min\left\{1, [1-(1-q_a)\Delta f\,]^{\frac{1}{1-qa}}\right\} \quad (5)$$

Where Δf and qa are the fitness difference and the acceptance parameter respectively.

B. Fuzzy Logic System

In 1965, Lotfi A. Zadeh introduced the concept of Fuzzy Logic, a mathematical tool designed to tackle real-world problems characterized by uncertainties.

Fuzzy logic has essential concepts that include fuzzy sets, granting elements the flexibility to belong to a set to varying degrees. Membership functions shape these sets, providing a framework for understanding through linguistic variables and terms. Fuzzy Logic Operations, including fuzzy AND, fuzzy OR, and fuzzy NOT, enable nuanced decision-making. Fuzzy rules are employed to articulate relationships between input and output variables. Fuzzification and defuzzification processes converting crisp values to fuzzy sets and vice versa. The inference mechanism integrates fuzzy rules, determining the extent to which each rule contributes to the final output.

Within the realm of fuzzy controller systems, there exist various types. In this paper, our specific focus will be on Larsen fuzzy controllers.

Larsen-type fuzzy controllers [7] utilize linguistic rules to define relationships between input and output variables. However, what sets Larsen controllers apart is their method of determining the membership values of the output fuzzy sets. Instead of using fuzzy implication, Larsen controllers employ a proportional scaling approach, where each rule contributes independently to the output. This scaling results in a set of output membership functions, reflecting the influence of each rule. The subsequent aggregation of these functions provides the final fuzzy output.

C. SA PARAMETER CONTROL USING FUZZY LOGIC

The performance of the SA algorithm heavily relies on the values assigned to its parameters, influencing the speed at which it converges. The primary innovation in our research lies in the comprehensive control of all key parameters for the Generalized Simulated Annealing (GSA), using fuzzy logic system with Larsen controllers with 10 rules (Figure1), encompassing not only the temperature and acceptance parameters but also extending to the local search operator. This control approach is particularly crucial as it directly influences the creation of new solutions for our SRFLP.

The control of qa and qT parameters involves utilizing the current temperature and fitness difference as input parameters. This dynamic adjustment mechanism ensures that the acceptance parameter and the temperature parameter respond dynamically to changes in temperature and the fitness landscape. By incorporating these real-time factors, our approach intelligently adapts these parameters, contributing to the versatility and adaptability of the optimization process. The membership function of qa and qT is defined based on [5] and [6] work and analysis.

Our proposed method incorporates local search operators, namely swap, insert, and scramble, each designed to bring about distinct effects on the solution. Specifically, we suppose that these operators exert varying levels of impact on the solution. The scramble operator, for instance, introduces a more substantial perturbation to the solution compared to the swap and insert operators. This nuanced differentiation in the perturbation levels adds a layer of sophistication to our approach, allowing for a tailored and effective exploration of solution space.

The fuzzy logic employed in our methodology adapts the choice of the operator based on several factors, including the similarity between the current and past solutions, the current temperature, and the fitness difference. This dynamic approach allows for the selection of a more suitable local search operator, aiming to generate an improved solution. The fuzzy logic system intelligently decides whether to apply a small, medium, or larger perturbation to the current solution, contributing to the overall efficacy of the optimization process.

The determination of solution similarity is quantified through the similarEdgesPercentage() function in Algorithm1. This function computes the percentage of shared edges between the current solution and the newly generated one. The generateSolution() function, crucial to our methodology, constructs a new solution based on the preceding one. The specific nature of the solution generated is dependent on the operator destruction value, a parameter regulated by the fuzzy logic system. This intelligent control mechanism influences the degree of perturbation applied to the solution, contributing to a nuanced exploration of the solution space.

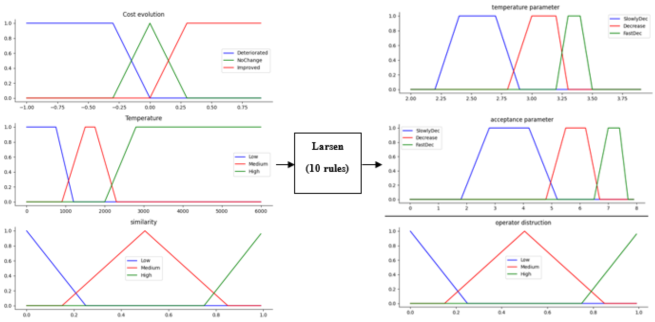

Figure 1. Fuzzy Logic system for SA parameters adaptation with fitness difference, current temperature and similarity between solutions as inputs and temperature parameter, acceptance parameter and operator destruction as output

Algorithm1: The proposed FLSA algorithm

Input: Objective functions f, Maximum number of iteration($MaxIter$), initial temperature T_init
Output: best solution for the objective functions f

Initialize parameters T_init, qa (acceptance parameter), qt (temperature parameter), op (operator_destruction_value)

$Ti \leftarrow T$_init
S ← initialSolution()
$Sbest \leftarrow S$

for i ← 1 to $MaxIter$ do
  S' ← **generateSolution**(op, S)
  Δf ← f(S') – f(S)
  normΔf ← normalize(Δf)
  similarity ← **similarEdgesPercentage** (S', S)
  if $\Delta f < 0$ or ($min\ \{1, [1-(1-qa)\Delta E]^{1/(1-qa)}\} >$ $random[0,1]$
    S ← S'
  end
  if f(S') < f($Sbest$):
    $Sbest$ ← S'
  end
  qt, qa, op←**fuzzyLogicController**(Ti, normΔf , similarity)
  $Ti \leftarrow T\_init \frac{2^{qt-1}-1}{(1+i)^{qt-1}-1}$

end

IV. PERORMANCE EVALUATION

To study the behavior of our improved FLSA, we tested it on several SRFLP benchmark instances. The proposed algorithm is compared with classical simulated annealing annealing (SA) with a cooling rate of 0.9999978. For both algorithms, the maximum iteration is 100, the initial temperature is 5000. The algorithms were tested on every instance 30 times using Python language, SciKit-Fuzzy library and run on a PC with Intel Core i5 2.30GHz processor and 4 GB of RAM.
The results in table show that FLSA give better solution compared to SA but has more computation time.

The statistical significance of the results was evaluated through the Wilcoxon signed-rank test at a significance level of 0.05. The p-values presented in Table 1 are greater than 0.05, suggesting a lack of statistical significance in the observed differences between SA and FLSA. Despite this, an effect size was identified (Table 1), indicating a practical significance in the performance divergence between the two algorithms. This implies that while the observed distinctions hold practical importance, they do not reach statistical significance given the current sample size.

TABLE I. PERFORMANCE OF THE SA COMPARED TO FLSA ON SRFLP INSTANCES

		FLSA	***SA***	***p-value***	***Effect size***
P15	Min Avg CPU	7269 8225.4 1.89	**6883** **8144.3** 0.73	0.48	36.14
P17	Min Avg CPU	**10351** **12409.4** 5.83	11568 12506.2 3.34	0.96	41.99
P18	Min Avg CPU	**12933.5** **14320.4** 5.69	13255.5 14754.3 4.85	0.016	21.36
P33-1	Min Avg CPU	**73961.5** **79226.1** 23.52	75634.5 79532.5 20	0.40	34.87
P33-2	Min Avg CPU	91998 98259.4 21.04	**87173** **97971.3** 18.15	0.98	42.17
P33-3	Min Avg CPU	**91048.5** **101983.4** 23.04	95863.5 102860 18.99	0.65	38.34

V. CONCLUSION

Our objective was to evaluate the effectiveness of fuzzy simulated annealing in tackling the Single Row Facility Layout Problem (SRFLP). Through a comparative analysis, we assess the performance of conventional simulated annealing versus its fuzzy-controlled counterpart using the Larsen method, considering various instances from benchmark datasets. The results show that our algorithm gives better solution compared to SA, which means that the fuzzy logic controller helps the SA search for better solution by controlling the local search operator type, the probability of the acceptance of the new generated solution and the cooling schedule. The findings underscore the efficacy of simulated annealing, further accentuated by the fuzzy controller, which significantly improves the algorithm's performance for the specified SRFLP instances. The study could be extended to assess FLSA's performance on larger SRFLP datasets and samples and compare its outcomes with other metaheuristic approaches.

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