Fuzzy Multi-Objective Transfer Problem Using Genetic Algorithm

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Abstract* - Therefore, planning and designing transmission networks is a fundamental topic in various scientific disciplines, including industrial and civil engineering. The Transfer Model (TM) constitutes a specific class of linear programming problems that addresses situations where goods are transported from sources (such as factories) to destinations (such as warehouses). This method combines fuzzy logic and genetic algorithms to enhance the design process. Goals are normalized using a multi-objective fuzzy method, enabling adjustment to function as a factor of the final objective function. The proposed genetic algorithm's evaluation necessitated a predetermined number of generations, which in this case was set to 12 generations. Upon analyzing these generations, it became evident that the algorithm converges to a nearly perfect solution. Consequently, the researcher conducted a special case study within a real production unit, specifically a meat production company, demonstrating favorable performance of the proposed model. The model comprises three main components: reducing travel distances between customers, minimizing distances between customers and the warehouse, and mitigating penalties for unmet customer demands. This paper presents an innovative and effective approach to address transmission network design based on reliability criteria. The results indicate an improvement in balancing task complexity and reducing overall path costs compared to similar methods. Overall, the findings demonstrate the superiority of the proposed algorithm over traditional methods in resolving problems of varying dimensions.

***Keywords* - Fuzzy Multi-Objective Transfer, Genetic Algorithm, Transport Network, Reliability Criterion.**

1 INTRODUCTION

The Markowitz model is a highly popular choice for determining movement patterns as it incorporates both risk and return criteria into the objective function by introducing the parameter λ (Chen et al., 2020; Birdawod, 2022). By employing a weighted summation approach and adjusting the value of λ between zero and one, the model effectively tackles multiple objectives.

The objective of this research is to minimize various parameters such as distance traveled, travel time, and the number of vehicles, ultimately maximizing customer satisfaction. However, the Vehicle Routing Problem (VRP) and Traveling Salesman Problem (TSP) belong to the category of NP-hard (nondeterministic polynomial time) or NP-complete problems. As the problem size increases, the computational complexity of known methods for finding optimal solutions grows exponentially, making it practically unattainable to find optimal solutions for real-world problems of large sizes. Instead, heuristic and meta-heuristic methods are employed to obtain acceptable and nearly optimal solutions.

The VRP is a dynamic and variable problem due to several influencing factors in real-world scenarios. Among the meta-heuristic algorithms, the Genetic Algorithm (GA) has been widely used to tackle the VRP. Specifically, our focus is on solving the more complex and challenging "Vehicle Routing with Random Demand (VRPSD)" using the GA approach.

2 STATEMENT OF THE PROBLEM

In this research, our focus is on finding the optimal solution for a multi-objective transfer problem. Various methods exist to address this challenge, such as ideal and interactive planning approaches, but they have their limitations. Another viable approach is the fuzzy method, where each objective is assigned a membership function, transforming the problem into a linear programming problem through the Belman-Zadeh minimum operator. The performance of this method is evaluated using a family of distance functions. To achieve a more comprehensive solution, we combine these three methods to determine the optimal outcome (Massoudi & Birdawod, 2023).

Our main objective is to minimize the distance between the worst upper limit and the best limit, resulting in an

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efficient solution. This is accomplished by adjusting the membership function values and expectation levels at each decision-making stage. The decision-maker's role is primarily limited to evaluating the effective solution and mitigating the impact of incomplete information.

The transportation issue involves minimizing costs while moving products from various origins to destinations, such as factories to warehouses or warehouses to supermarkets. To solve this problem, the simplex algorithm is utilized. However, in practical scenarios, costs and supply-demand quantities are represented as fuzzy numbers, necessitating a fuzzy approach to determine optimal values for transporting goods between origins and destinations. Our thesis proposes a novel algorithm to address transportation problems in a completely fuzzy context. It transforms the transportation problem into a three-objective problem and utilizes a weighted approach to solve multi-objective problems. Ultimately, a new problem is tackled using the simplex approach. The proposed approach will be applied to real-world data as part of our research.

In modern times, transportation planning holds significant importance across various scientific disciplines, particularly in the realms of industrial engineering and civil engineering. As mentioned earlier, the overarching objective of transportation planning is to enhance service quality, ensure greater safety, minimize energy consumption, and contribute to economic advancement.

3 LITERATURE REVIEW AND RELATED RECORDS

In his article, Hitchcock initially drew attention to transportation matters, focusing on cost minimization between origins and destinations (Ekanayake et al., 2022). His transportation system design solely took into account the two aspects of origin and destination. However, in numerous transportation scenarios, goods are transported using multiple modes such as airplanes, trucks, ships, and trains. Hence, it becomes essential to also consider the selection of the appropriate transportation mode. This academic paper offers a comprehensive overview of diverse transportation-related challenges and mathematical models. These resources can effectively address various business issues associated with product distribution, commonly known as transportation problems.

In 2023, Devnath et al. (2023) focused on addressing a specific type of 3D transportation problem known as the fixed-cost 3D transportation problem, which considers both variable and fixed costs associated with goods transportation. In a paper from 2013, Classical TSP (CTSP) along with its variant Random TSP (RTSP) were solved using various meta-heuristic algorithms, and their performance was compared based on tour length (Gupta, 2013). Among these approaches, handling the first type of fuzzy sets proved particularly challenging. To effectively manage uncertain information and utilize it in practical applications, numerous researchers have proposed enhanced theories, including type-2 fuzzy sets, which offer fuzzy membership functions capable of describing and extracting valuable hidden information. Essghaier et al. (2023) introduced the concept of the Physical Internet (PI), aimed at improving supply chain efficiency and sustainability, especially in cross-docking operations. This research specifically addresses truck scheduling in rail-road PI-Hubs, taking into account uncertainty and multi-objective decision-making. The proposed model, named Multi-Objective Mixed-Integer Programming (FMO-MIP), integrates fuzzy chance-constrained programming to minimize delays and container travel distances, while considering uncertainties in truck arrival times.

This approach fills a research gap and provides a robust decision-making solution that aligns with risk attitudes and balances conflicting objectives (Essghaier et al., 2023) and (Sheah, 2021).

The introduction of the type-2 fuzzy set by Zadeh & Aliev (2019) in 2019 brought about an extension to the first type fuzzy set. This extension was further developed by Liu and Liu in 2020 using validity theory. Unlike type-3 fuzzy sets, where the degree of membership is a definite number between -1 and 1, type-2 fuzzy sets represent the degree of membership for each element as a fuzzy set. In other words, instead of using a single number, type-2 fuzzy sets employ intervals in their membership functions to define the degree of membership. This characteristic grants a higher level of flexibility in handling uncertainties compared to type-3 fuzzy sets (Abed and Al-Salami, 2021).

Kacher & Singh (2024) introduce a two-step generalized parametric approach for fuzzy parameter-based multi-objective transportation problems with uncertain data. The method seeks multiple optimal solutions, offering decision-makers various options. First, fuzzy data is partitioned into distinct levels using parametric equations. Second, fuzzy programming techniques solve the CMOTPs for different values, generating multiple optimal solutions.

Gulia & Kumar (2024) developed distance-based methods for multi-objective optimization problems using fuzzy and non-fuzzy approaches. These techniques address vector-maximum problems with multiple objectives by minimizing the gap between

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ideal and feasible goals. FMOLPP are tackled using various fuzzy and non-fuzzy methods, with ranking functions handling ambiguity for precision.

In 2020, researchers (Wang et al., 2020) recognized that as urban spaces continue to evolve, transportation within these spaces becomes increasingly complex. Many challenges arise when trying to reach destinations efficiently and quickly while minimizing disruptions. Balancing the need for reliable communication routes and minimizing costs poses a significant dilemma, as these objectives often conflict with each other. To address this issue, the researchers developed an integer programming model that focuses on the direction and location of the routes. This model aims to find a logical balance between the conflicting goals and takes a positive step towards resolving them. To showcase the valuable results obtained from this model, a study sample was utilized.

Type-2 fuzzy sets have emerged as a significant theory in environments characterized by high levels of uncertainty, enabling the reduction of their impact and providing effective modeling approaches. The utilization of type-2 fuzzy sets has been extensively explored in various real-world problems, including transportation issues, as noted by Heisdal (Mardani et al., 2019) and (Abdul-Zahra, 2016). Konishi et al. (2024) utilized a fuzzy classifier, one of the most widely used and interpretable artificial intelligence techniques, to reduce model complexity while simultaneously maximizing classification accuracy. This was achieved by applying fuzzy genetics-based machine learning (MoFGBML) within the framework of multi-objective evolutionary optimization algorithms (EMOAs).

In their 2022 study, Al-Salami and colleagues developed a model for inventory control using a Genetic Algorithm (GA). This GA-based model aims to minimize the Total Annual Inventory Cost (TAIC) function, which is specifically tailored for the proposed approach. The researchers customized the GA to determine the optimal reorder level for perishable food items. To validate the model's effectiveness, a case study was conducted at a five-star hotel in Iraq. Additionally, a sensitivity analysis was performed to evaluate the model's robustness across varying reorder levels. By employing the GA, the study successfully achieved a minimum inventory cost while identifying the optimal reorder level. The results confidently demonstrate that the proposed GA significantly reduces the monthly inventory cost by effectively determining the ideal reorder level (Al-Salami et al., 2022).

Artificial Neural Networks (ANNs) lead modern AI and machine learning research by capturing non-linear relationships and complex data patterns, excelling where linear models fail. They continuously improve with more data, automatically extracting relevant features without explicit engineering. GAs evolve a population of potential solutions to find optimal or near-optimal results for complex problems, applicable to both single-objective and multi-objective optimization. The combination of ANNs and GAs is versatile, and effective in various domains such as optimization, pattern recognition, and predictive modeling, as demonstrated by Xie et al. (2024) in optimizing a microchannel heat sink.

Sahib & Kovács (2024) employed an Artificial Neural Network (ANN) in conjunction with a Genetic Algorithm (GA) to develop a multi-objective optimization model, integrating Monte Carlo simulation for a range of industrial applications. The primary aim was to minimize both the cost and weight of composite sandwich structures.

In 2020, Kanda and colleagues (Bagheri et al., 2020) treated each arc in a Fuzzy Flexible Multi-Objective Transportation Problem (FFMOTP) as a decision-making unit, generating multiple fuzzy outputs through multiple fuzzy inputs. Subsequently, by employing the common set of weights (CSW) concept in Data Envelopment Analysis (DEA), they established a distinct fuzzy relative efficiency for each arc, thereby introducing the notion of 3D multi-product and multi-objective transportation within a fuzzy environment.

Prior to that, in 2016, Liu and colleagues (Bai & Liu, 2016) proposed an optimization method incorporating uncertainties encountered in the manufacturing industry. The main motivation behind building this optimization model is to provide tools for producers to develop robust supply chain network designs. They devised a solution for the 3D transportation problem using type-2 fuzzy parameters to achieve an optimal solution. Their approach involved considering transportation costs, supply, demand, and transport vehicle capacity as type-2 fuzzy numbers. Using various methodologies, they successfully transformed the type-2 fuzzy variables into type-3 fuzzy variables.

Kundu et al. (2014) were pioneers in tackling this issue. They began by employing critical value (CV)-based reduction methods to transform type-2 fuzzy variables into type-1 fuzzy variables, aiming to obtain the corresponding defuzzified values of the type-2 fuzzy cost parameters. Following this, the centroid method was utilized to achieve comprehensive defuzzification. They explored the concept of fixed-cost transportation, where the involved parameters were represented as type-2 fuzzy numbers (Jameel and Al-Salami, 2023).

Building upon this work, in 2015, Pramanik and colleagues formulated models to address similar issues. These models were formulated as profit maximization problems, where specific Distribution Centers (DCs) were selected to satisfy demands at all retailers. Type-2 fuzziness was eliminated by utilizing a generalized credibility measure developed through CV-based reduction methods. Consequently, the models were transformed into chance-constrained programming problems with various credibility labels. Additionally, they extended the study to include a two-stage supply chain network with type-2 Gaussian fuzzy variables, aiming to maximize profits (Pramanik et al., 2015).

In a separate 2015 study, Kalf et al. introduced a fuzzy multi-objective framework designed to address challenges in aggregate production planning. The framework targets scenarios involving multiple products, time periods, and uncertain conditions. The objective is to minimize both overall production cost and labor cost. The researchers introduced a novel approach based on Zimmerman's method, which effectively determines tolerance and aspiration levels. Real-world data from an industrial company were utilized to validate the proposed model, demonstrating its feasibility. The findings indicate that the introduced method is practical, adaptable, and capable of solving aggregate production planning problems with varying parameters (Kalaf et al., 2015).

In the following year, researchers (Bai & Liu, 2016) delved into supply chain network design using type-2 fuzzy variables. Their objective function was based on the value at risk of total costs, employing the theory of fuzzy possibility and credit size definition. Furthermore, in 2017, Kumar Jana and colleagues utilized reduction techniques to convert type-2 fuzzy variables into type-3 fuzzy variables, effectively addressing transportation issues within a supply chain network (Jana et al., 2017; Nawkhass & Birdawod, 2017).

In 2018, Das and colleagues (Das et al., 2018) put forward several theorems along with their proofs in their research paper. Moreover, they applied the proposed defuzzification process by formulating a new multi-objective green solid transportation model, where all parameters were represented as trapezoidal type-2 fuzzy variables. The primary objectives of this model include maximizing profits and minimizing carbon emissions generated by the modes of transportation, which are influenced by factors such as their loads, fuel type, engine type, and driving characteristics. They also proposed a method for defuzzifying trapezoidal type-2 fuzzy variables, which they applied to solve the multi-objective 3D green transportation problem with type-2 fuzzy parameters.

In 2020, Kondo and colleagues created multiple scenes for input purposes. In their study, the authors identified that the lighting arrangement is significantly affected by five key factors: the scene's context, the Point-of-View, the intensity of the light sources, the camera's position, and the characters' emotions. These elements are collectively termed the SPICE system, representing situation, POV, intensity, camera, and emotion (Hassan et al., 2024). The authors' proposed SPICE system automatically incorporates extra light sources into the scene based on the scenario and director's actions. Furthermore, the study investigated the topic of 3D transportation of multiple goods, incorporating type-2 fuzzy parameters (Andreas et al., 2020).

4 RESEARCH METHOD

The objective function in (2022) has been defined using a range of parameters, which have been incorporated into the proposed method. The following are the descriptions of signs and parameters employed in defining the objective function (Selvam et al., 2022).

$$Max\ \mu = \lambda\mu_{Return} + (1-\lambda)\mu_{Risk} \qquad \dots (1)$$

Which $Return_{\mu}$ is the value of the membership function related to the return objective function and Risk μ is the value of the membership function related to the capital risk objective function, which are calculated by the fuzzy approach.

4.1 Multi-objective fuzzy method

Within this project, a multi-objective fuzzy approach is employed to normalize the objective functions, resulting in their weighted sum being incorporated as the ultimate objective function. In this approach, the membership functions of the subsequent relationships are utilized in sequence, specifically for the objective functions aimed at minimizing risk and maximizing return (Al-Salami and Abdalla, 2022).

$$\mu_{EQ} = \begin{cases} 1 & EQ < EQ_{min} \\ \frac{EQ_{max}}{EQ_{max} - EQ_{min}} & Q_{min} \le EQ < EQ_{max} \\ 0 & EQ > EQ_{max} \end{cases} \qquad \dots (2)$$

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$$\mu_{ER} = \begin{cases} 0 & ER < ER_{min} \\ \frac{ER - ER_{min}}{EQ_{max} - EQ_{min}} & ER_{min} \leq ER < ER_{max} \\ 1 & ER > ER_{max} \end{cases} \quad \dots (3)$$

Where μ and R represent the value of the objective functions related to risk and return, respectively. The description of data collection we can see it in Figure (1) below.

This paper aims to optimize the selected model using a well-suited genetic flowchart. The flowchart follows a series of steps outlined below:

1. Determine the parameters of the flowchart, including the selection operator, mutation and intersection operators, their rates, and the number of generation repetitions, which serve as the termination condition.
2. Establish limits, such as the maximum number of shares in the basket.
3. Generate the initial population for the genetic flowchart.
4. Evaluate the fitness of each member of the initial population using the fitness function.
5. Select and assign the fittest individuals to the optimal set.
6. Apply intersection and mutation operators.
7. Verify compliance with the defined limits.
8. Extract the best solution.
9. Check if the termination condition has been met.
10. If the termination condition is satisfied, conclude the flowchart; otherwise, repeat from step 4.

These steps can be depicted graphically in an exponential process, forming the genetic flowchart as shown in the above diagram.

4.2 Determine the fitness function

The fitness function evaluates the suitability of each chromosome. When applying a genetic algorithm to an optimization problem, the fitness function assigns a value to each chromosome, which then influences the selection process. In our case, the fitness function is designed to consider the lowest values for both the total distance and the number of unfulfilled client requests. Consequently, chromosomes with lower fitness values have a higher likelihood of being selected due to their improved performance in terms of minimized distance and unmet client requests.

4.3 Search form

In our proposed approach, transportation is dynamic, meaning that customer demands are not predetermined, but rather determined when the vehicle arrives at each customer's location. To effectively meet these demands, the problem must be formulated in a manner that can accommodate these unknown requirements. This adaptability to address varying demands contributes to the problem's stability, as it enhances the problem's ability to respond to different demand scenarios. The higher the problem's stability coefficient, the more resilient and flexible it is in accommodating diverse demand situations.

4.4 Data collection

To assess the effectiveness of the meta-algorithms presented in this study, a set of experimental problems with varying dimensions are randomly generated. The performance of these algorithms is then evaluated by comparing their solution quality and computation time. The values for parameters such as order registration time by visitors, travel time between stores, and weighting factor for stores are randomly generated using a standardized distribution, as illustrated in the table below. These randomly generated values serve as input data for the experimental problems.

5 A CASE STUDY

With the rapid progress of urbanization and manufacturing industries, coupled with changing societal interests and behaviors, the task of market recognition and acquiring a valuable market share has become increasingly complex. Resolving this challenge is crucial for the viability, dynamism, and sustainability of any group in the current landscape.

To effectively compete and gain market share in various sectors, both service and production companies require a well-established sales and distribution system. Consequently, it is essential to carefully consider factors such as appropriate store allocation for salespeople and the suitable orientation for each seller in order to achieve the aforementioned objectives.

Unfortunately, many organizations tend to rely on empirical methods within their sales departments, which primarily focus on quantitative variables such as the number of customers per visit. However, this approach overlooks crucial parameters like the skill level of salespeople, resulting in a decline in productivity and motivation among the sales force.

In this research, the researcher aims to enhance the motivation of salespeople and facilitate the achievement of sales goals and organizational growth by providing optimal guidance and considering their skill levels. To

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examine this issue, a real production unit specializing in roasted meat will be investigated in detail in the following section.

The Bryan Gosh company, the focus of this study, was established in July 1400 on a 6,000 square meter plot of land in the second phase of Amol Industrial City. It possesses an annual production capacity of 3,000 tons, offering a variety of meat products such as red meat and chicken burgers, kebabs, fast food items including falafel, cutlets, and other meat varieties, as well as various packaged grilled chicken and chicken products (Jami et al., 2023). With guidance from reputable monitoring and evaluation firms, Brian Gosht's company has successfully obtained multiple quality control certifications, including GMP, HACCP, (ISO 9001) 2020, ISO 10002, and Iranian Standard.

The sales department of Bryan Gosh consists of four sales representatives responsible for serving 161 units within the city. The geographical location of the company is depicted in Figure (2). Empirical data from the company has been collected for problem analysis. Due to the extensive amount of information available, its inclusion in this section has been omitted. However, the relevant information is provided in the attached CD format. The proposed algorithms have been employed to solve the aforementioned problem, and the calculated results obtained from addressing this practical issue are presented in Table (2).

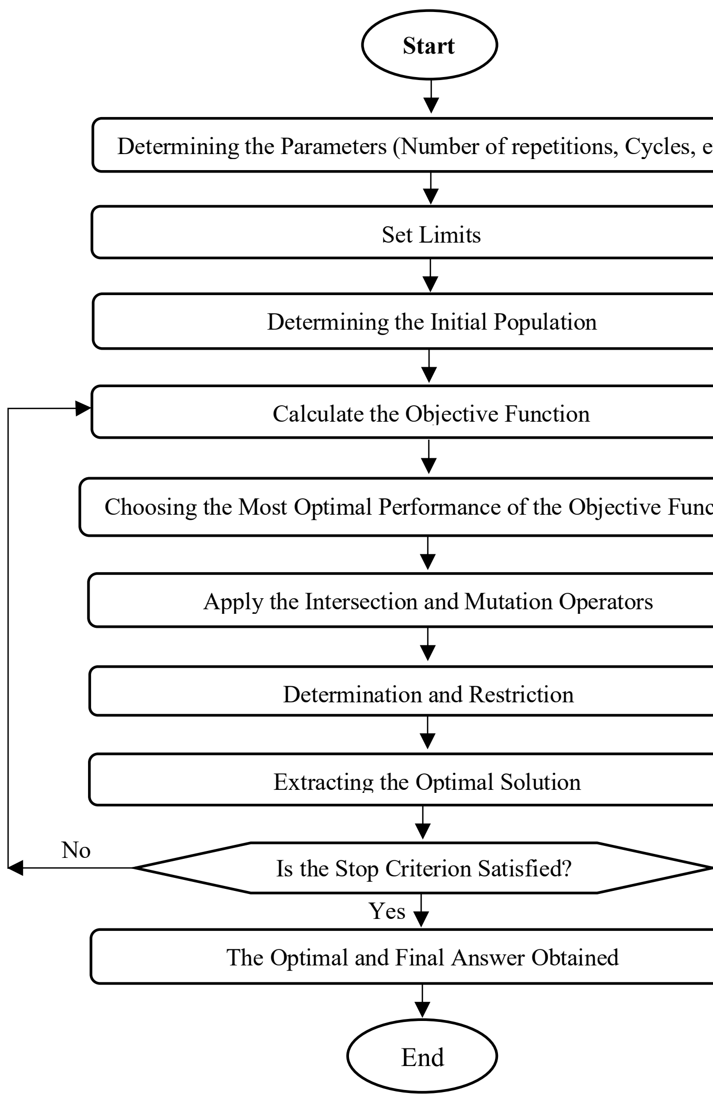

Fig. 1. Description of data collection

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TABLE 1
Data input values to experimental problems

U~ [30 50]	Time Of Demand by Visitors for Unit Type A
U~ [15 30]	Time Of Demand by Visitors for Unit Type B
U~ [5 15]	Time Of Demand by Visitors for Unit Type C
U~ [7 30]	Travel Time Between Units
U~ [2 4]	Unit Weight Factor

6 THE PROPOSED METHOD

Our proposed method addresses the uncertainty of customer demand, emphasizing the inherent ambiguities within the problem and bringing it closer to real-world practical scenarios. A key aspect of our approach is to generate stable solutions in such conditions and employ the most effective methodologies. Notably, customer requests remain unknown until the vehicles reaches their location. Based on the customer demand and the current load of the vehicle, the car determines its course of action. If the customer's demand can be accommodated within the existing load, the customer is serviced, and the vehicle proceeds to the next customer. This process continues until all customers have been served. However, if the vehicle's current load falls short of meeting the customer's demand, a negative cost (penalty) is assigned, prompting the vehicle to return to the warehouse for reloading. After reloading, the vehicle resumes serving the remaining customers. The practical applications of the proposed method are extensive and can be observed in various real-life situations that frequently arise.

6.1 Formula of the proposed form

This section presents the mathematical model designed to minimize the conventional costs associated with Vehicle Routing Problem (VRP). These costs include the path cost, reload cost, and unserved request cost. The solution proposed by the model determines the optimal vehicle routing considering customers with unknown demand. The formula and subsections of this part have been slightly modified and adapted from (Abu-Monshar et al., 2021; Visutarrom & Chiang, 2019).

6.2 Check the closeness

In this study, the stopping criterion for the algorithm was defined based on the number of generations. Once the predetermined number of generations is reached, the algorithm terminates. Specifically, our proposed method employs a total of 20 generations. After this designated number of generations, the Genetic Algorithm (GA) converges towards a near-optimal solution for the problem at hand. The implementation of the proposed algorithm was carried out using MATLAB software version 7.12.0 (R2019a) on a Pentium® computer with a clock speed of 2.6 GHz. For access to the code, please refer to the attached file.

6.3 Define the problem

To achieve an optimal workload distribution among salespeople, the problem of guiding visitors is formulated by taking into account factors such as the salespeople's skills, varying visit durations, and transfer times between units. The aim is to strike the ideal balance by considering the individual skills and experience of each salesperson.

A set of n feature stores, $N = \{1,2, \ldots, n\}$ visited by V visitors $V = \{1,2, \ldots, v\}$ such that only one visitor visits each store. Each salesperson is restricted to visiting a single store at any given time, while each store is open to visits from all salespeople. Additionally, each store can only be visited once within a specific time period, known as the visit time. The timing of store visits by the salespeople is influenced by both the type of store and the individual capabilities and skills of the salesperson. The objective of this research is to determine the optimal allocation of store visitors and the most effective sequence of store visits for each salesperson. This optimization aims to minimize the workload discrepancies among the salespeople, ensuring a more balanced distribution of tasks.

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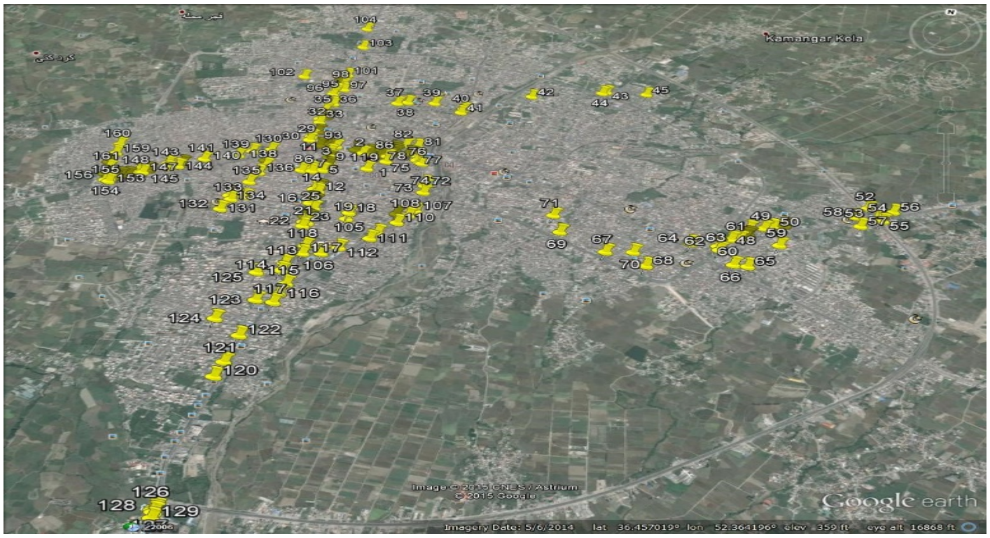

Fig. 2. An aerial photograph of 1,610 units that were examined

6.4 Indicators

$V: the\ number\ of\ visitors$
$N: the\ number\ of\ clients$
$i,j: customer\ index\ i,j = 1,2,...,N$
$v: visitor\ index\ v = 1,2,...,V$

6.5 Form input parameters

Vt_{iv} : The time of registering the visitor′s request (v_m) in the store i_m
S_{ij}: Travel time from store i_m to store j_m.
$F_{iV} = (Vt_{iv})/w_i$: Potential load.
$w_i: store\ weight\ factor\ im.$
L: A large positive number

6.6 Decision-making variables

X_{ijv} : $if\ visitor\ v\ goes\ from\ client\ i\ to\ j\ set\ (1).$
Y_{jv}: $If\ the\ client\ is\ j\ of\ the\ visitor's\ v, it\ is\ set\ (1), otherwise\ (0).$
C_{jv}: $It's\ time\ to\ complete\ the\ visit\ j_m\ by\ visitor\ v_m.$
C_{max}
: $Maximum\ time\ to\ complete\ my\ visit\ before\ visitors.$
C_{ji} and C_{max} $variables\ including\ non$
$-\ negative\ real\ values\ and\ variables$
X_{jmi} and Y_{jki} $are\ of\ types\ zero\ and\ one.$

6.7 Determinants

$$\sum_{i=0}^{n}\sum_{v=1}^{v} x_{ijv} = 1,\ \forall\, i \neq j;\ j = 1 \dots N \qquad \dots (4)$$

This limitation ensures that each shop is visited by only one visitor and at one location on the tour.

$$\sum_{i=0}^{n} X_{ijv} = y_{jv},\ \forall\ i \neq j;\ j = 1 \dots N;\ v = 1 \dots V \quad \dots (5)$$

This limitation states that if the j_m client is assigned to the v_m visitor, it must come directly after the node, which can be directly after the repository location.

$$\sum_{j=1}^{n} X_{ijv} \leq y_{jv},\ \forall\ \mathrm{i} \neq \mathrm{j};\ i = 1 \dots N;\ v = 1 \dots V \quad \dots (6)$$

This constraint ensures that if the client (node or store) i is assigned to the visitor, at most one node will come immediately after it.

$$\sum_{v=1}^{n} y_{iv} = 1, \quad \forall\ \ i = 1 \dots N \qquad \dots (7)$$

This restriction ensures that each node is assigned to a single visitor.

$$C_{jv} - C_{iv} + L(1 - x_{ijV}) \geq S_{ij} + F_{jv}, \quad \forall \begin{array}{c} i = 1 \dots N \\ i \neq j = 1 \dots N \\ v = 1 \dots V \end{array} \qquad \dots (8)$$

According to this constraint, the time required for the most capable visitor, *v*, to complete service at node *j* is equivalent to the time it takes for the same visitor to complete service at the preceding node, i. This time includes factors such as the travel time to reach node *j* and the service time at node *j*. The specific duration is determined based on the skill level of each visitor and the quality level associated with each node.

$$C_{jv} \geq x_{ijv}.S_{ij} + F_{Jv}.y_{jv}, \quad \forall \begin{array}{c} j = 1 \dots N \\ v = 1 \dots V \end{array} \qquad \dots (9)$$

The above constraint states that the completion time of each node is greater than the service time and the time to reach the requested node.

$$C_{1v} = 0, \quad \forall\, v = 1,..,V \qquad \dots (10)$$

Lastly, this constraint implies that the time required to complete tasks at the warehouse is assumed to be zero. Taking into account the explanations provided above, the mathematical model proposed in this study can be presented as Eq. (11).

6.8 Estimate the total cost

In the context of VRPSD (Vehicle Routing Problem with Stochastic Demand), the objective is to determine an optimal route that minimizes the expected travel

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distance for a vehicle based at a warehouse with a capacity of Q. The total cost involved in the problem comprises several factors, including:

- The travel cost between each pair of customers.
- The cost of returning to the warehouse for recharging if the customer's demand exceeds the current vehicle capacity.
- The cost of traveling from the warehouse to the subsequent customer after servicing the current customer.
- The penalty incurred due to the failure to serve a customer.

$$
\left.
\begin{aligned}
&Min\ Z = C_{max}\\
&Subject\ to:\\
&\quad \sum_{i=0}^{n}\sum_{v=1}^{v} x_{ijv} = 1,\ \ \forall\ (i \neq j;\ \ j = 1 \ldots N)\\
&\quad \sum_{i=0}^{n} X_{ijv} = y_{jv}\ ,\ \ \forall\ \ (i \neq j\ ;\ j = 1 \ldots N;\ v = 1 \ldots V)\\
&\quad \textstyle\sum_{j=1}^{n} X_{ijv} \leq y_{jv}\ ,\ \ \forall\ \ (i \neq j\ ;\ i = 1 \ldots N\ ;\ v = 1 \ldots V)\\
&\quad \textstyle\sum_{\mathrm{v}=1}^{\mathrm{n}} \mathrm{y}_{\mathrm{iv}} = 1,\ \ \forall\ \ (i = 1 \ldots N)\\
&\quad \textstyle\sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{x}_{0\mathrm{jv}} \leq z_v\ ,\ \ \forall\ (v = 1 \ldots V)\\
&\quad \textstyle\sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{x}_{0\mathrm{jv}} \leq\ z_v - 1\ ,\ \ \forall\ (v = 1 \ldots V)\\
&\quad C_{jv} - C_{iv} + L\big(1 - x_{ijV}\big) \geq S_{ij} + F_{jv},\ \ \forall(i = 1 \ldots N; i \neq j = 1 \ldots N;\ v = 1 \ldots V)\\
&\quad C_{jv}\ \geq x_{ijv}.S_{ij} + F_{Jv}.y_{jv},\ \ \forall(j = 1 \ldots N;\ v = 1 \ldots V)\\
&\quad C_{1v} = 0\ , \forall(v = 1 \ldots V)
\end{aligned}
\right\} \ldots (11)
$$

7 VALIDATE THE FORM

In this section, we will validate the proposed formulation by conducting a test problem. Due to the absence of a standardized example in the literature that incorporates the mentioned constraints, a random problem instance is generated. The details of this experimental problem are provided in Tables (2) and (3), involving a total of 6 stores and 2 visitors.

TABLE 2
Test problem data for each node

	N =2; V = 6					
Node	1	2	3	4	5	6
Vt_{i1}	25	10	8	15	16	7
Vt_{i2}	20	15	13	22	25	15
$Level$	A	C	C	B	B	C
w_i	2	2	2	3	3	2

To obtain the optimal solution and perform a thorough analysis of the problem, we utilized the MATLAB program to solve the aforementioned experimental problem. The results obtained from this computation are presented in Table (4). Notably, the MATLAB program successfully derived the globally optimal solution to the problem within a time frame of 240 seconds.

From Table (4), it is evident that the workload of the first visitor is 28.5147, while the workload of the second visitor is slightly higher at 32.8383. The difference between the workloads is relatively small. Furthermore, based on the table and the assigned variable values, we observe that the first visitor begins their route from the repository by visiting node number 5, followed by nodes 4, 3, and 6, respectively. Conversely, the second visitor

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starts by visiting node #1 and then proceeds to node #2. As anticipated, a larger number of nodes are assigned to the first visitor, considering their higher level of experience, resulting in shorter visit durations at each node.

Considering the similarities between the problem investigated in this study and the scheduling problem of unrelated parallel machines, specifically in terms of task sequencing and reducing the maximum completion time, it is important to examine the problem's complexity within the context of scheduling. Many synthetic problems, including most scheduling problems, are classified as *NP-hard* problems. These problems typically lack polynomial algorithms capable of providing reasonable computation time for their solutions. Applying the concept of heuristics and meta-heuristic algorithms becomes highly effective in addressing scheduling problems that fall into the realm of complex problems. These approaches allow for the attainment of near-optimal solutions within a reasonable timeframe.

In this paper, we address a scheduling problem involving parallel machines where the objective is to minimize the maximum task completion time by considering task sequencing without constraints on setup times. This type of scheduling problem, which does not involve minimizing the maximum completion time, is known to be a challenging NP problem.

To assess the performance of the proposed meta-algorithms, we present 12 experimental problems classified into small-scale (8 problems) and medium-to-large-scale (12 problems) categories. The results of solving these problems using the algorithms are provided in tabular format throughout the remaining chapters. For the small-scale problems, we employed MATLAB software to evaluate the algorithms and compare the quality of their solutions against the optimal solutions. It is important to note that the execution time for the MATLAB program was set to a maximum of 3 hours. If a problem could not be solved within this time frame, the best solution obtained within the 3-hour limit was reported.

The complexity of a problem refers to the number of calculations required by a solution algorithm to reach the optimal solution, and it is studied in a branch of computer science called complexity theory. If the problem size increases, the time required to solve the problem by the solution algorithm follows a polynomial algorithm, then the solution algorithm is of polynomial degree.

For example, in a problem of size n (where n represents the amount of information required to determine the problem), the number of calculations required to solve the problem is limited by an upper limit that is a function of n. In this scenario, as the value of n increases, the number of calculations required using the problem-solving algorithm is in the form of a polynomial function of n, indicating that the solution algorithm is of polynomial degree. Under the same conditions, polynomial algorithms are generally faster than non-polynomial algorithms, and their performance is more justified.

Since the problem investigated in this research is quite similar to the scheduling problem of unrelated parallel machines with the limitation of the preparation time depending on the sequence of tasks with the aim of minimizing the maximum time to complete the tasks, therefore, from a scheduling perspective, the complexity of the investigated problem should be examined. Many important combinatorial problems, such as most scheduling problems, belong to the class of NP-hard problems. The level of complexity of these problems is such that usually there are no polynomial algorithms capable of solving them in a reasonable computing time. The application of this concept is highly effective in solving scheduling problems that fall into the class of complex problems, as solving such problems typically requires heuristic and meta-heuristic algorithms to reach the optimal solution within a reasonable time.

Furthermore, we conducted five runs of each of the proposed algorithms on all eight small-scale problems and twelve medium-to-large-scale problems. The results obtained from each algorithm for each problem instance include the worst, average, and best solutions, along with the corresponding computation time. The implementation of the solution algorithms was carried out in the MATLAB R2021b programming environment, utilizing a PC equipped with an Intel(R) Core(TM) i7 CPU operating at 2.4GHz and 8GB memory. Based on the findings presented in Table (5), it is clear that the algorithm outperformed the genetic algorithm in terms of solution quality. The results demonstrate that both algorithms determined the optimal paths and sequences of store visits for each visitor. Let us now delve into the specific outcomes obtained by the algorithm. The algorithm allocated 50 stores to the first visitor, who is considered the most proficient, while assigning 35, 42, and 34 stores to the subsequent visitors, respectively. Essentially, the algorithm aimed to assign nearby shops within the same area to each visitor, promoting efficiency and convenience in their routes.

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TABLE 3
Data of the experimental problem related to the interval between groups

Node S_{ij}	0	1	2	3	4	5	6
0	0	8	6	8	10	6	8
1	0	0	3	7	6	7	12
2	0	3	0	6	4	4	10
3	0	7	6	0	2	6	5
4	0	6	4	2	0	2	6
5	0	7	4	6	2	0	5
6	0	12	10	5	6	5	0

TABLE 4
Visit completion times for each node in the experimental problem

Node visitor	1	2	3	4	5	6
1	-	-	24.3333	18.3333	11.3333	32.8383
2	18	28.5147	-	-	-	-

TABLE 5
Calculation results from solving problems of medium to large dimensions

	Problems	GA				ACO			
Problems	N×M	Bad	Middle	Best	Time	Bad	Middle	Best	Time
1	2×12	121.16	118.08	111.5	18	116.41	113.46	111.5	11
2	3×15	100.33	98.26	96.33	20	94.5	92.38	87.83	16
3	3×18	115.08	112.61	109.33	22	112.58	109.21	107.16	21
4	2×20	191.08	188.16	184.91	23	175.23	171.21	167.16	20
5	4×20	109.58	102.38	92.5	24	107.08	100.34	95.83	22
6	3×25	166.45	152.18	143.33	30	148.91	145.06	140.5	32
7	2×30	268.58	260.09	253.5	40	250/41	249.23	247.25	40
8	4×30	150.33	139.84	134.91	42	143.08	137.79	134.41	44
9	5×40	155.58	151.66	141.16	44	158.66	151.46	142.66	48
10	2×50	419.41	414.31	404.16	50	394	391.14	389.66	60
11	4×50	243.5	230.73	215	52	227.91	217.12	203.91	61
12	4×60	294.5	279.79	266.91	60	280.5	274	269.66	73

8 CONCLUSION

The problem of optimization and vehicle routing (VRP) is one of the basic problems in this field of our research and is considered a gateway to entering and solving some issues related to transportation and its operations. This involves designing and optimizing routes for a fleet of vehicles to serve specific customers. One of the critical criteria used in the proposed method, our research focuses on improving time and energy consumption in this field of research. Instead of using the traditional measure of path length (the number of hops), the criterion of the distance between two points or solutions was used. Our decision to use this type of algorithm was motivated by the fact that existing algorithms struggle to handle solving VRP problems on a large scale within a reasonable time frame. To address this, we used the current proposed method resulting from or hybrid fuzzy compilation of multi-objective functions to transform the large problem into smaller sub-problems and solve them smoothly. Then apply the genetic algorithm to search the solution space and find solutions for each sub-problem separately.

The results obtained from this approach indicate that the combined use of the optimal genetic algorithm and

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the multi-objective fuzzy method accelerates the convergence of solutions, and prevents the algorithm from getting stuck in local minima. Despite the large computational burden imposed by the problem, the proposed method demonstrates low computational complexity, as confirmed by the proposed experimental results.

Furthermore, some of these suggestions are presented as follows:

1. Considering the vehicle's ability to determine the appropriate route during peak sales periods.
2. Evaluating the salespeople's skills as a dynamic factor that changes over time, to analyze the learning effect on this parameter.
3. Factoring in time windows to account for the satisfaction level of stores.

REFERENCES

Abed, F., & Al-Salami, Q. H. (2021). Calculate the best slope angle of photovoltaic panels theoretically in all cities in Turkey. *International Journal of Environmental Science and Technology*, 1-16.

Abu-Monshar, A., Al-Bazi, A., & Al-Salami, Q. H. (2021). On the Development of a Multilayered Agent-based Heuristic System for Vehicle Routing Problem under Random Vehicle Breakdown. *Cihan University-Erbil Scientific Journal*, *5*(1), 1–10.

Al-Salami, Q. H., & Abdalla, S. N. (2022). The impact of academic satisfaction as a mediator on international conferences. *Cihan University-Erbil Journal of Humanities and Social Sciences*, 6(1), 19-26.

Al-Salami, Q. H., Saleh, R. K., & Al-Bazi, A. F. J. (2022). An Efficient Inventory Model-Based GA For Food Deterioration Products In The Tourism Industry. *Pesquisa Operacional*, *42*.

Andreas, A., Hariadi, M., Purnomo, M. H., & Kondo, K. (2020). Two Stage Fuzzy Inference Systems for Autonomous Lighting in 3D Animated Movie Scene. *International Journal of Intelligent Engineering & Systems*, *13*(5).

Bagheri, M., Ebrahimnejad, A., Razavyan, S., Hosseinzadeh Lotfi, F., & Malekmohammadi, N. (2020). Solving the fully fuzzy multi-objective transportation problem based on the common set of weights in DEA. *Journal of Intelligent & Fuzzy Systems*, *39*(3), 3099–3124.

Bai, X., & Liu, Y. (2016). Robust optimization of supply chain network design in fuzzy decision system. *Journal of Intelligent Manufacturing*, *27*, 1131–1149.

Birdawod, H. Q. (2022). Using factor analysis to determine the most important factors affecting student absenteeism at Cihan University-Erbil. *Cihan University-Erbil Scientific Journal*, *6*(2), 1-8.

Chen, B., Zhong, J., & Chen, Y. (2020). A hybrid approach for portfolio selection with higher-order moments: Empirical evidence from Shanghai Stock Exchange. *Expert Systems with Applications*, *145*, 113104.

Das, A., Bera, U. K., & Maiti, M. (2018). Defuzzification and application of trapezoidal type-2 fuzzy variables to green solid transportation problem. *Soft Computing*, *22*(7), 2275–2297.

Devnath, S., De, M., Mondal, S. S., & Maiti, M. (2023). Two-stage multi-item 4-dimensional transportation problem with fuzzy risk and substitution. *Journal of Ambient Intelligence and Humanized Computing*, 1–28.

Ekanayake, E., Daundasekara, W. B., & Perera, S. P. C. (2022). An examination of different types of transportation problems and mathematical models. *American Journal of Mathematical and Computer Modelling*, *7*(3), 37–48.

Essghaier, F., Chargui, T., Hsu, T., Bekrar, A., Allaoui, H., Trentesaux, D., & Goncalves, G. (2023). Fuzzy multi-objective truck scheduling in multi-modal rail-road Physical Internet hubs. *Computers & Industrial Engineering*, 109404.

Gulia, P., & Kumar, R. (2024). Distance-based methods for multi-objective optimization problems: Fuzzy and non-fuzzy approaches. *AIP Conference Proceedings*, *2986*(1).

Gupta, D. (2013). Solving tsp using various meta-heuristic algorithms. *International Journal of Recent Contributions from Engineering, Science & IT (IJES)*, *1*(2), 22–26.

Hassan, A. M., Alomari, M. A., Al-Salami, Q. H., Alqurashi, F., Flayyih, M. A., & Sadeq, A. M. (2024). Numerical analysis of MHD combined convection for enhanced CPU cooling in NEPCM-filled a trapezoidal cavity. *International Communications in Heat and Mass Transfer*, 159, 108343.

Jameel, A. M., & Al-Salami, Q. H. (2023). Principal Component Analysis Technique for Finding the Best Applicant for a Job. *Cihan University-Erbil Journal of Humanities and Social Sciences*, *7*(1), 121-125.

Jami, M. S., Massoudi, A. H., & Al-Salami, Q. H. (2023). Ethical leadership role in job embeddedness and job involvement. *Cihan University-Erbil Journal of Humanities and Social Sciences*, 7(1), 11-15.

Jana, D. K., Pramanik, S., & Maiti, M. (2017). Mean and

DOI: http://doi.org/10.24086/icafs2025/paper.1767

CV reduction methods on Gaussian type-2 fuzzy set and its application to a multilevel profit transportation problem in a two-stage supply chain network. *Neural Computing and Applications*, *28*, 2703–2726.

Kacher, Y., & Singh, P. (2024). A generalized parametric approach for solving different fuzzy parameter based multi-objective transportation problem. *Soft Computing*, *28*(4), 3187–3206.

Kalaf, B. A., Bakar, R. A., Soon, L. L., Monsi, M. Bin, Bakheet, A. J. K., & Abbas, I. T. (2015). A modified fuzzy multi-objective linear programming to solve aggregate production planning. *International Journal of Pure and Applied Mathematics*, *104*(3), 339–352.

Konishi, T., Masuyama, N., Casillas, J., & Nojima, Y. (2024). Fairness-aware Classifier Design via Multi-objective Fuzzy Genetics-based Machine Learning. *2024 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, 1–8.

Kundu, P., Kar, S., & Maiti, M. (2014). Fixed charge transportation problem with type-2 fuzzy variables. *Information Sciences*, *255*, 170–186.

Mardani, A., Hooker, R. E., Ozkul, S., Yifan, S., Nilashi, M., Sabzi, H. Z., & Fei, G. C. (2019). Application of decision making and fuzzy sets theory to evaluate the healthcare and medical problems: a review of three decades of research with recent developments. *Expert Systems with Applications*, *137*, 202–231.

Massoudi, A. H., & Birdawod, H. Q. (2023). Applying knowledge management processes to improve institutional performance. *Cihan University-Erbil Journal of Humanities and Social Sciences*, *7*(1), 1-10.

Nawkhass, M. A., & Birdawod, H. Q. (2017). Transformed and solving multi-objective linear programming problems to single-objective by using correlation technique. *Cihan International Journal of Social Science*, *1*(1), 30-36.

Pramanik, S., Jana, D. K., Mondal, S. K., & Maiti, M. (2015). A fixed-charge transportation problem in two-stage supply chain network in Gaussian type-2 fuzzy environments. *Information Sciences*, *325*, 190–214.

Sahib, M. M., & Kovács, G. (2024). Multi-objective optimization of composite sandwich structures using Artificial Neural Networks and Genetic Algorithm. *Results in Engineering*, *21*, 101937.

Selvam, A., Mayilswamy, S., Whenish, R., Naresh, K., Shanmugam, V., & Das, O. (2022). Multi-objective optimization and prediction of surface roughness and printing time in FFF printed ABS polymer. *Scientific Reports*, *12*(1), 16887.

Visutarrom, T., & Chiang, T.-C. (2019). An evolutionary algorithm with heuristic longest cycle crossover for solving the capacitated vehicle routing problem. *2019 IEEE Congress on Evolutionary Computation (CEC)*, 673–680.

Wang, C., Liu, J., Li, H., Nai, W., & Zheng, W. (2020). Driving risk evaluation applied to premium actuary for pay-how-you-drive vehicle insurance based on fuzzy multi criteria decision-making. *2020 IEEE 11th International Conference on Software Engineering and Service Science (ICSESS)*, 457–462.

Xie, Y., Nutakki, T. U. K., Wang, D., Xu, X., Li, Y., Khan, M. N., Deifalla, A., Elmasry, Y., & Chen, R. (2024). Multi-objective optimization of a microchannel heat sink with a novel channel arrangement using artificial neural network and genetic algorithm. *Case Studies in Thermal Engineering*, *53*, 103938.

Zadeh, L. A., & Aliev, R. A. (2018). *Fuzzy logic theory and applications: part I and part II*. World Scientific Publishing.

DOI: http://doi.org/10.24086/icafs2025/paper.1767