HEURISTIC-BASED ALGORITHMS FOR MATHEMATICAL MODELING OF DEVELOPMENT AND PERFORMANCE

Sunilkumar S.Badiger

Lecturer (Selection Grade)

Govt.polytechnic, MUDHOL

ABSTRACT

Scheduling is the practice of assigning a number of tasks to a new line while utilizing constrained resources to achieve approved goals. Brand-new Scheduling in manufacturing is allocating n newline tasks to the available m machines to fulfill both times- and cost-based newline objectives, such as new line minimization of the manufacture span, tardiness, lateness, due date, and so on. Since manufacturing newline industries play an essential role in a country's economy, constructing an effective scheduling system to boost growth rates and newline productivity becomes a top priority. In order to solve multi-objective subtask newline scheduling issues in manufacturing, this work attempts to provide an efficient newline scheduling approach and a mathematical model. The several aims are taken into account in a newline. In this study, the total weighted completion time for customer order scheduling is minimized, the load balance and cost for industrial robots are minimized, and a solid mathematical model for the problem of customer order schedule is developed. We investigated the issue size for optimality using a mixed integer linear programming model with mixed composition to minimize the newline makespan. Cost, time, and quality are the three main goals of the newline framework for the Service Selection and Optimization Scheduling Problem (SSOSP), together with transportation time and cost and manufacturing cost and time. To accomplish the objectives above, this study used heuristic-based algorithms like the Artificial Immune System (AIS), Particle Swam Optimization (PSO), Subtask Scheduling Algorithm (SSA), and Fuzzy based min-max rule algorithm.

Key Words: Artificial Immune System, Particle Swam Optimization, Subtask newline Scheduling Algorithm.

INTRODUCTION

The increasing complexity in the manufacturing industry and growing interest in bio immune and Meta heuristic based technologies for solving multi-objective subtask scheduling problems has driven interest in this research. It is good to accurately describe the general representation and mathematical model of the proposed heuristic-based algorithms. This chapter explains basic concepts of working mechanisms, mathematical representation, and the applications ofheuristic-based algorithms such as Artificial Immune System (AIS), Particle Swam Optimization (PSO), Subtask Scheduling Algorithm (SSA), and Fuzzy based min-max rule algorithm.

ARTIFICIAL IMMUNE SYSTEM (AIS)

AIS is an artificial intelligence technique that has been used to solve scheduling problems for over ten years. To solve problems, AIS is inspired by vertebrate immunology theory, immune functions, working principles, and immune system mechanisms. It complements existing pattern recognition, design, modeling, and control techniques by acting as a powerful tool. Optimization, device and network protection, scheduling, data processing, mining, and fault and anomaly detection are the major application domains of AIS. In AIS, the learning process is based on interactions between antibody and antigen populations, which results in a particular self-organizing network structure. Each AIS corresponds to a specific number of potentials in the solutions presented. Other essential features of AIS include the ability to produce innovative solutions quickly, inbuilt memory management, robust recognition, and self-tolerance. Because of these outstanding features, researchers have begun to use AIS to solve multi-objective scheduling problems. Finding a schedule that reduces the application's overall completion time is the primary goal of any scheduling problem. Each solution is an antibody (Ab); several libraries will be generated, each containing several genetic strings that are part of scheduling problem solutions. An antibody (schedule) is generated by concatenating threads from individual libraries.

The best specific found was cloned thousands of times. The clones were swapped out, and the best clone was chosen as the solution to the problem.

The Immune System (IS) is a built-in defensive mechanism that shields all living things from external threats. IS has a biological nature that is resilient, adaptable, and capable of dealing with a wide range of disruptions and uncertainties. The innate and adaptive immune systems are the two main components of this system. The innate consists of organs that protect the body from external attacks, such as skin and mucus. Phagocytes found in the body's tissues and blood assist these protective organs. Phagocytes often send out a signal when they detect a threat. These defensive components are responses to a broad category of problems with a limited and predetermined set of responses. If the natural defense elements fail to respond to threats, adaptive is called to respond to the infectious agent. The most vital part of this mechanism is white blood cells (lymphocytes), which are created by the bone marrow.

The two types of lymphocytes are B-cells, made in the bone marrow, and T-cells, made in the thymus. B-lymphocytes produce antibodies, and some of themlive on as memory cells. T-lymphocytes interact with other cells to survive. T-cells are classified into two types: helper T-cells that activate B-cells and destroyer T-cells that kill intracellular pathogens. B-cells that have been stimulated send antigen pieces to destroyer T-cells. Immune recognition takes place between the receptor's area and an epitope. Antibodies bind to several molecules on the infectious agent's surface rather than the entire infectious agent. The immune system's mechanism is depicted in Figure 1.

Antibodies are two-part molecules with variable and constant regions. The IS can speed up the adaptation process due to variations in the variable field. According to research on antibody diversity produced during the immune response, the number of somatic mutations in the variable region rises over time. The antibody's affinity for the antigen increases as a result. Mutation levels at high levels play an essential role in IS maturation. The hypermutation mechanism is random; several antigens will be destroyed during the mutation process. The population of high-affinity antibodies must be increased for the IS to address this issue effectively. Therefore, the selection is essential for developing formative high-affinity antibodies.

There are a plethora of theoretical models focused on the IS mechanism. Bone-marrow models, Negative selection models, and Clonal Selection dependent algorithm models are the most commonly used models. The selection of these models depends entirely on the problem's existence. We used a Clonal selection-based algorithm to find the best solution to our research dilemma. The following is a thorough summary of the same model.

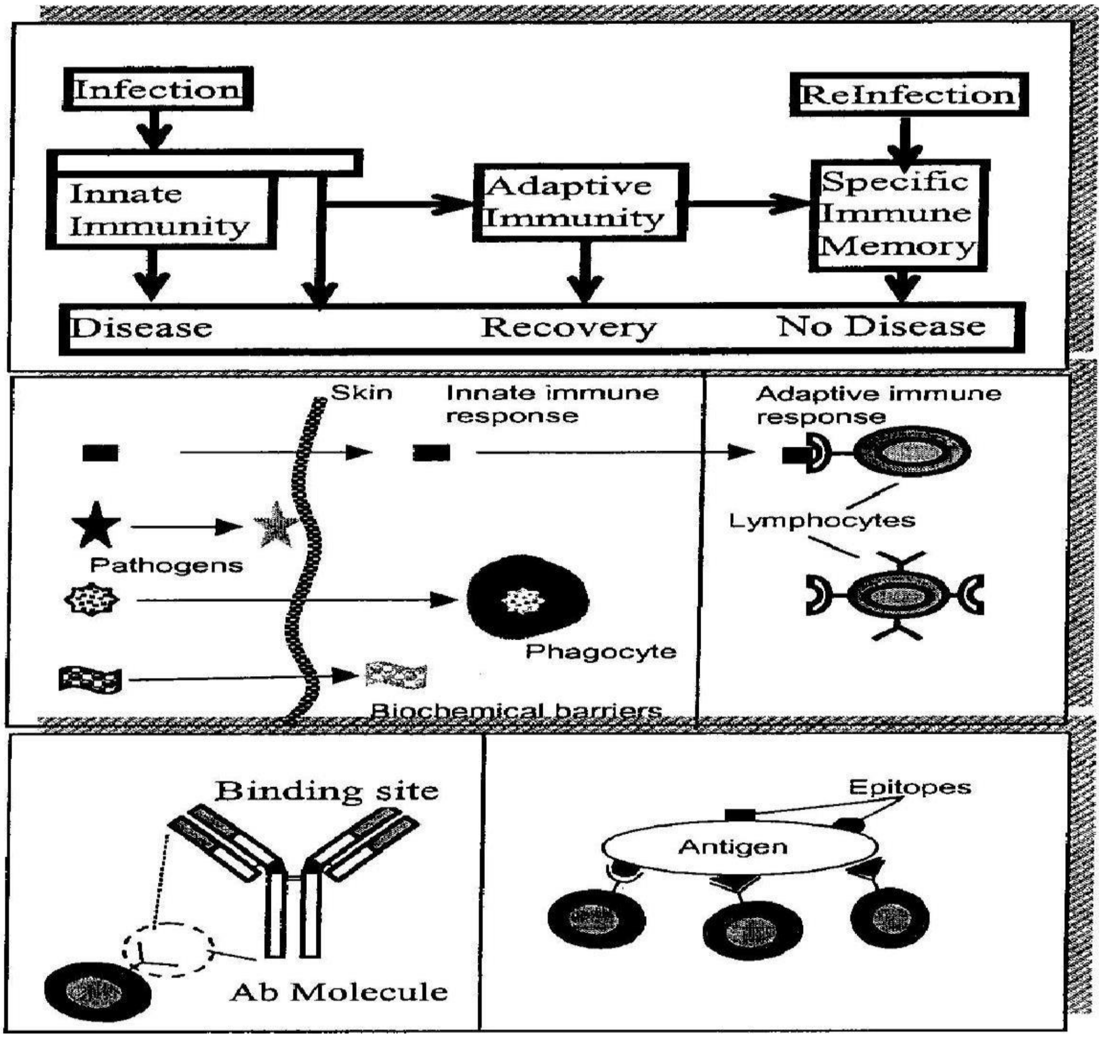

Figure - 1 IS function flow (Top), Defense in the immune system (Middle), and Immune recognition (Bottom)

CLONAL SELECTION PRINCIPLE

The antigen-determined affinity maturation process of B-cells and the related hypermutation mechanism are the foundation of the clonal selection concept. Two key ideas were covered by De Castro et al. [26] in their discussion of affinity maturation in B-cells. According to the first principle, the similarity of the antigen that binds to a B-cell's representative develops an attraction, producing more clones. The second opinion states that the mutation undergone by the antibody of a B-cell is contrary wise relative to the attraction of the antigen it binds. Using these two principles, they developed one of the broadly used Clonal selection-based AIS algorithms called CLONALG **(Figure 2)**.

The following factors were taken into account when creating the clonal selection-based algorithm; collection and cloning of efficient stimulated cells, affinity mutation and recollection of the clones with high affinity, hypermutation of cells proportional to their affinity, preservation of the memory cells, a decrease of non-stimulated cells, production and preservation ofdiversity.

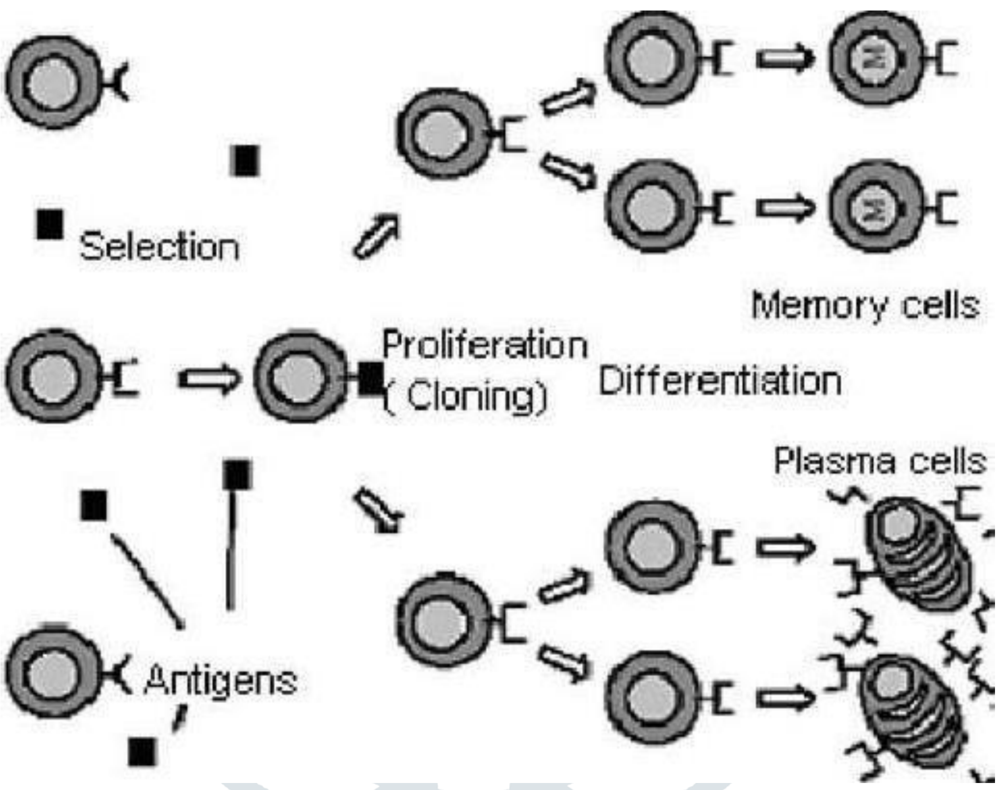

Figure - 2 Clonal selection principle

The antibody is an entrant agenda in the algorithm, and the antigen is a participant agenda, which will be the best until the algorithm creates a prompt. The stepwise working procedure of the algorithm is given below.

Step 1: Generate an initial antibody population that generates potential schedules.

Step 2: Obtain the affinity of the generated antibodies.

Step 3: Generate clones for each antibody; the calculation of the number of clones to be generated dependson the affinity of the respective antibody.

Step 4: Generate maturated cloned population by hypermutation process.

Step 5: Choose the best clone and discard the remaining clones.

Step 6: Considered the new population as the candidate for the next generation.

This mechanism is continued till the best solution is obtained. This is the best schedule for theoptimal problem, meeting the pre-defined constraints.

PARTICLE SWAM OPTIMIZATION (PSO)

The social behaviors of animals like a flock of birds or a school of fish inspired the evolutionary population-based intelligence approach known as particle swarm optimization (PSO). PSO technique was proposed. The remarkable characteristics of PSO, specific optimization through social evolution, its ease of use, the simple mathematical operators it requires, and its low cost in terms of both memory requirements and time have led researchers to pay more attention to this technique. Here are a few applications that have implemented the PSO technique are; chemical engineering, data mining, the voltage control problem, environmental engineering, pattern recognition to solve Scheduling problems, and task allocation.

The PSO algorithm is analogous to the existing EA. In PSO, the number of particles represents the population in a problem space. Particles are randomly initialized. Every generation must strive to maximize the fitness function, which determines the fitness values for every particle. Each particle's best position, designated as pbest, represents the best fitness value (outcome) the particle has ever achieved. The best particle fitness in a population is represented by the best position within the entire group of particles denoted by gbest. The size of the population is problem-dependent. The most available sizes considered are 20–50. In each generation, the velocity and particle position will be calculated using Equations 1 and 2, respectively. The initial velocity's inertia is the first component of Equation 1. The second component, cognition, denotes individual thought, while the last component, social awareness, denotes interparticle collaboration. Equation 2 states that the particle's new position is obtained by adding the new velocity to the current position.

$$V_{i,k+1} = wV_{i,k} + (rand)_1 C_1 (P_i - X_{i,k}) + (rand)_2 C_2 (P_g - X_{i,k}) \quad (1)$$

$$X_{i,k+1} = X_{i,k} + V_{i,k+1} \quad (2)$$

Where,

$$\left[\begin{array}{c} "i = i^{th} particle \\ X_{i,k} = position\ of\ partcle\ 'i'\ in\ iteration\ 't' \\ V_{i,k} = velocity\ of\ particle\ 'i'\ in\ iteration\ 't' \\ p_i = previous\ best\ position\ of\ particle\ 'i' \\ P_g = previous\ best\ position\ among\ all\ the\ particles (g_{best}) \\ w = inertial\ weight - balances\ local\ and\ global\ exploitations\ of\ the\ particles \\ C_1 and C_2 = learning\ factors - controls\ the\ influence\ of\ p_{best} and g_{best} on\ search\ process \\ (rand)^1 and (rand)^2 = random\ numbers - taken\ within\ the\ range\ [0,1]" \end{array}\right.$$

The summarized process for standard PSO is as follows:

Step 1: Create a population of all the particles at random initial speeds and positions.

Step 2: Estimate the suitability ideals of all elements, set the *gbest* of each unit to its existingplace, and set the *gbest* identical to the place of the best original element.

Step 3: Calculate the velocity and position of each particle using Eqs. (1) and (2).

Step 4: Determine the fitness values for each particle and contrast them with their pbest values. Update pbest with the current position and fitness value if the present value is superior.

Step 5: Find the population's best particle with the highest fitness value. The best particle should be used to update the gbest if the fitness value is superior to it.

Step 6: Output gbest and its fitness value if the maximum number of iterations is reached; otherwise, proceed to Step 3.

SUBTASK SCHEDULING ALGORITHM

Customers' preferences and specifications are complex as a result of mass customization. As a result, it is more prudent to concentrate on multi-task scheduling to have the best services and please customers. Multi-tasks can be classified into two categories: homogeneous and heterogeneous multi-tasks. The homogeneous task has identical characteristics and can be completed using the same manufacturing processes. When working on a heterogeneous mission, the features are not all the same and must be processed through various processes. Decomposing a task into various subtasks and processing them by aggregated distributed resources is the best way to manage heterogeneous multi-tasking (Figure 3).

Task decomposition is dividing a large piece of work into two or smaller tasks, known as subtasks. The working organization of insect societies served as a general inspiration for this. Many animals, such as ants, bees, termites, and wasps, engage in mission decomposition. Almost all of the insects listed above are foragers. Time and money are factors in task decomposition. The profit comes from either improving individual performance or improving the overall system. The honey bee's nectar accumulation is the best example of mission decomposition. Foragers carry nectar to bees working inside the nest, known as receivers, who then deposit the nectar into cells. As a result, nectar selection is decomposed among foragers and receivers. Task decomposition causes a novel feature: transportation between forager and recipient, by dividing the task – nectar selection – into two subtasks: foraging and receiving.

The resources required to link each subtask in a decomposed mission. Linking related tasks is required for task decomposition. A task is a discrete piece of work that needs to be completed. Foraging encompasses the collection, repossession, and storage of forage. The job is incomplete if forage is gathered and taken halfway to its storage location. The full completion of work is, in general, dependent on several tasks. Due to the heterogeneous relationship between subtasks in a process, several structures are created when a task is decomposed into several subtasks. These structures are converted into tree structures,which offer only aggregation relationships and make it simple to explain the types of processes. The decomposition of tasks is a relatively recent concept. A task's division into smaller tasks and distribution among the available resources are essential because they significantly influence the output.

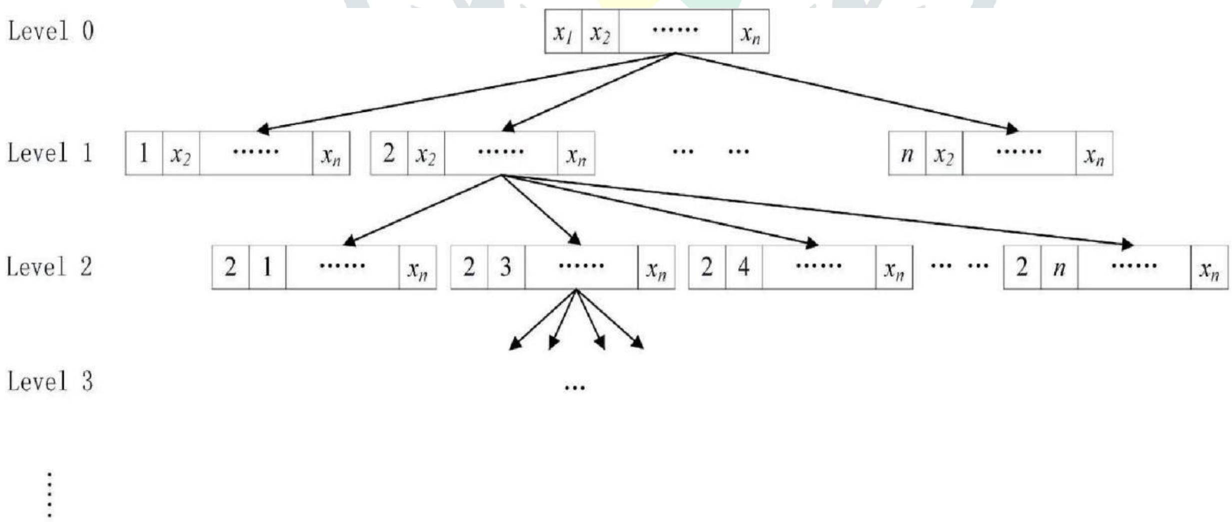

Figure -3 Decomposition of a task into several subtasks

Several articles have been published in recent years to advance the effectiveness and usefulness of task decomposition methods by Pi *et al.* [69]. A detailed description of the subtask scheduling algorithm is discussed in chapter 6; here, we will give the basic concept followed in developing the subtask scheduling algorithm.

BASIC CONCEPT OF SUBTASK SCHEDULING (TASK DECOMPOSITION)

1) Partitioning: The existing most promising task is decomposed into several subtasks. Each approximation and the leftover solutions are aggregated into the nearby task.

Random Sampling: Several samples are chosen randomly from each subtask and the nearby task. Depending on the problem, different schemes for sampling can be used. However, the probability of selecting each solution must be positive, and high-quality solutions are preferred when sampling.

2) Evaluation of the Promising Index: The sample objective function values are evaluated for each subtask and nearby task; based on these values, the promising indices are determined.

3) Backtracking: Based on the promising indices of the subtask and the nearby task, the most promising task in the successive approximation is determined. If the most promising index corresponds to a subtask, then that subtask becomes the most promising task in the successive approximation. Backtracking is performed if the most promising index corresponds to the nearby task.

FUZZY-BASED MIN-MAX RULE ALGORITHM

Scheduling is assigning limited resources within the constraints to meet well-defined objectives. Feasible scheduling satisfies the constraints associated with tasks and available resources. Researchers find more significant challenges in obtaining feasible scheduling in a multi-processor scheduling environment. Many techniques are proposed to address these challenges, like AIS algorithms (as discussed in the previous section) and Fuzzy techniques. In this section, we will discuss scheduling problems using the fuzzy technique.

Fuzzy logic was proposed by Zadeh [98] and has applications in target detection, image analysis, computer science, intelligent information processing, etc. Boolean logic can be replaced with fuzzy logic, which uses the degree of actual value to observe the mode of reasoning and is crucial for decision-making in uncertain and imprecise situations. Fuzzy inference consists of three stages as follows:

1. Input Stage: Receives input such as target line, completing time, response time, etc., and mapsthese inputs to suitable membership functions.

2. Processing Stage: Each applicable rule is invoked, and the corresponding results are producedand joined to give input to the output stage.

3. Output Stage: Converts the joined result back into a specific value.

The membership function depicts a curve showing how each input is mapped to a membership value between 0 and 1. The processing stage is based on several logical rules. The logical rules are stated in IF-THEN rules (in detail, if- the rules are discussed in the next session). In order to understand the fuzzy inference technique, it is more relevant to know some basic definitions of a fuzzy concept, which are given below:

BASIC DEFINITIONS

Fuzzy set:

Fuzzy set is expressed as a Membership function μ_A which maps all the members in universal set Y *to* $\{0, 1\}$. Denoted as $\mu_A : Y \rightarrow \{0,1\}$

In fuzzy sets, each one of the element is mapped to [0, 1] by membership function $\mu_A : Y \rightarrow [0,1]$, [0, 1] is the real numbers between 0 and 1 including 0 and 1.

Operations on Fuzzy set:

Among various operators, the standard operators are complement, Maximum (Max) and Minimum (Min) are the fundamental and simple operators. A range of fuzzy theories are developed based on these operators.

Complement set *A*, union $A \cup B$ and intersection $A \cap B$ are the standard operations of fuzzy theory and are defined as,

$$\mu_{\bar{A}}(x) = 1 - \mu_A(x)$$

$$\mu_{A \cup B}(x) = Max\ [\mu_A(x), \mu_B(x)]$$

$$\mu_{A \cap B}(x) = Min\ [\mu_A(x), \mu_B(x)]$$

Fuzzy Rule representation-Inference:

The process of obtaining new information by drawing on previously known information is known as inference. The most popular inference used is of the form "if-then." Illustrated as

"If x is a, then y is b."

The antecedent (if applicable) and consequent make up the rule, which is interpreted as an implication. Example: If "x is a," we can deduce that "y is b" is the case.

Fuzzy if-then Rules:

Typically, a fuzzy rule has the following form: "If x is A, then y is B."

A and B, respectively, are linguistic values specified as fuzzy sets on the discourse universes X and Y. A fuzzy implication or fuzzy conditional statement are other rules. Part x is A and is referred to as the "antecedent" or premise, while part y is B and is referred to as the result or conclusion. Let's define the meaning of the word R: "If x is A, then y is B," before we use fuzzy if-then rules to represent and evaluate a system.

This is sometimes abbreviated as R: A - B

The expression describes the relationship between the two variables, x and y. This implies that a fuzzy rule is a binary relation R on the X x Y product space.

Fuzzification:

Performs the following operations and converts input values into fuzzy values.

- Has access to the input values
- Transforms input variable values into corresponding discourse universe
- Creates fuzzy sets from the provided statistics.

Defuzzification:

A control command is often provided as a crisp value in programs. As a result, the result of the fuzzy inference has to be defuzzified. One must first undergo defuzzification to get a non-fuzzy control action that best captures the possible distribution of a fuzzy control action. Unfortunately, choosing a good defuzzification strategy is not a systematic process; instead, it depends on the characteristics of the application.

Min-max algorithm:

This principle is based on fuzzy set theory that provides a common method for extending crisp domains of mathematical expressions to fuzzy domains. This method generalizes an ordinary mapping of a function to a mapping between fuzzy sets.

Suppose that g is a function from X to Y, and A is a fuzzy set on X defined as

$$A = \{(x_1, \mu_A(x_1)), (x_2, \mu_A(x_2)), \ldots\ldots\ (x_n, \mu_A(x_n))\}$$

Then the principle states that the Composition of fuzzy relations R and S

$$SR = SoR\ \{(x, y), \mu_{SR}(x, z)\}$$

Where $\mu_{SR}(x, z) = \min\ \max\ \{(\mu_R(x, y)), (\mu_S(y, z))\}$

CONCLUSION

In this research paper, we discussed the basic concept and working mechanism of heuristic-based algorithms such as AIS, PSO, and SSA, as well as the fuzzy concept in scheduling. Many researchers have been drawn to AIS because of its ability to produce new solutions in a short period, as well as its robust identification and self-tolerance. Similarly, the PSO algorithm has advantages due to its ease of use and the fact that it only includes basic mathematical operators. The subtask scheduling algorithm is helpful in the case of multiple heterogeneous tasks with different scheduling characteristics that various processes must process. In order to obtain feasible scheduling, fuzzy-based algorithms are applied in a multi-processor scheduling system, where researchers face more significant challenges. Algorithms can be chosen and applied based on the problem's goal and the scheduling design.

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