AN INTEGRATED APPROACH BASED ON FUZZY INFERENCE SYSTEM FOR SCHEDULING AND PROCESS PLANNING THROUGH MULTIPLE OBJECTIVES

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ABSTRACT. Integrated process planning and scheduling (IPPS) problems are one of the most important flexible planning functions for a job shop manufacturing. In a manufacturing order to produce \( n \) jobs (parts) on \( m \) machines in a flexible manufacturing environment, an IPPS system intends to generate the process plans for all \( n \) parts and the overall job-shop schedule concurrently, with the objective of optimizing a manufacturing objective such as make-span. The optimization of the process planning and scheduling will be applied through an integrated approach based on Fuzzy Inference System (FIS), to provide for flexibilities of the given components and consider the qualitative parameters. The FIS, Constraint Programming (CP) and Simulated Annealing (SA) algorithms are applied in this design. The objectives of the proposed model consist of maximization of processes utility, minimization of make-span and total production costs including costs of flexible tools, machines, process and TADs. The proposed approach indicates that The CP and SA algorithms are able to resolve the IPPS problem with multiple objective functions. The experiments and related results indicate that the CP method outperforms the SA algorithm.

1. Introduction. In many manufacturing systems, considering the flexibility in operations is on an increase together with a focus on the optimum use of production resources. Synchronization of scheduling and process planning is inevitable. Traditionally, scheduling and process planning are implemented as two sequential decision-making functions in a manufacturing system. Both process planning and scheduling functions are accountable for the efficient allocation and utilization of resources in manufacturing systems. Process planning determines the selection and sequence of production operations, together with the essential manufacturing resources, including machines and tools. The purpose of scheduling is to allocate the jobs and operations to limited manufacturing resources in accordance with the process plan. Integrated process planning and scheduling (IPPS) is to bridge the gap between process planning and scheduling in order to improve the performance of both functions and make the manufacturing system more responsive to dynamic competitive space. There exist a limited number of studies on IPPS. Due to the combination of the two optimization problems and the flexibilities in the manufacturing systems thereof, large-scale IPPS problems are difficult to solve through analytical
approaches, Zhang et al. [14]. IPPS problems are mostly NP-hard which are difficult to solve by traditional analytical methods with limited computing time. Some researchers have resorted to approximate methods like meta-heuristics for solving the IPPS problem. Meta-heuristic methods are widely adopted to solve complex combinatorial optimization problems. However, some objectives related to jobs sequencing, which are difficult to assess, like goodness of machines proximity in a process plan, are considered less due to their ambiguous and imprecise nature.

The Fuzzy Inference System (FIS) is one of the most famous applications of fuzzy logic and fuzzy sets theory and is applied in process simulation or control, Zadeh [13]. They can be designed either from expert knowledge or qualitative data. Designing a FIS based on both datasets can be run in two main phases: automatic rule generation and system optimization. Rule generation leads to a basic system with a given space partitioning and a corresponding set of rules, while system optimization can be run at various levels.

In this study, optimization of the process planning and scheduling will be applied through an integrated approach based on FIS, Constraint Programming (CP) and simulated annealing (SA) algorithms. An attempt is made in this study to introduce the machine, tool, sequence, and tool direction access flexibility, in a multi-objective model through qualitative parameters with respect to the choice of process design. The objectives include maximization of process utility, minimization of make-span and total production costs, including costs of flexible tools, machines, process and tool approaching directions (TAD). Qualitative parameters are considered based on FIS for the calculation of process utility. To assess the quality and validity of the model outcome, the problem is solved through SA algorithm and CP method and the solutions are compared.

The model design is presented in Sec. 3; the application of the proposed model based on simulating annealing algorithm and Constraint Programming model is introduced in Sec. 4; the computational results are presented in Sec. 5 and the article in included in Sec. 6.

2. Literature review. The process planning and scheduling are performed separately and sequentially, Li et al. [5]. There exists a great volume of literature on the respective separate approaches of process planning and scheduling. Integration of these activities is an effective solution to avoid extra costs that cause changes in existing flexibility in order to improve the performance of the system. The studies run on reconfigurable process planning and process plan flexibilities are on an increase in order to meet the needs of dynamic and flexible manufacturing space, Zhang et al. [14]. Different meta-heuristics are applied to solve the IPPS problems, Li et al. [5], revealed a SA optimization approach to optimize the integrated process planning and scheduling, where, flexibility of sequential, process and timing performance metrics include average time components, the level of balanced exploitation, production costs and delays in production orders are of concern.

Wan. [11], applied the ant colony approach with regards to the launch time to solve the problem of integrated process planning and scheduling optimization, where the external sources (independent producers) are of concern. Shen et al. [9], proposed a mathematical modeling and multi-objective evolutionary algorithms for dynamic and flexible job shop scheduling problems. Zhanjie et al. [16], used a genetic algorithm with crossover and mutation operators for the optimization of integrated process planning and scheduling and applied the optimal production process flexibility in the given workshops gain.
Wang et al. [12], applied particle swarm optimization (PSO) algorithm for multi-objective integrated process planning and scheduling problems. They applied numerical experiments to find a collection of high-quality business solutions to show the effectiveness of (PSO). Zhang et al. [14], applied the formulation and implementation of constructive meta-heuristics for solving (IPPS) problems, where, a model is established to express that IPPS problems through AND/OR graphs, then a generic framework is proposed for implementing constructive meta-heuristics in the solution model, followed by adopting Ant colony optimization (ACO) as a representative example for illustrating the implementation. Experimental results of the benchmark problems indicate that the effectiveness and high performance of their proposed approach is based on the integration of the generic framework and ACO strategy. Zhang et al. [15], proposed an object-coding genetic algorithm (OCGA) to resolve the IPPS problems in a job shop type of flexible manufacturing system (FMS). An unusual selection and a replacement strategy are integrated systematically for the population evolution, with the objective to achieve near-optimal solutions through gradual improvement of the overall quality of the population, instead of exploring neighborhoods of good individuals. They reveal that their proposed genetic algorithm can yield outstanding outcomes for complex IPPS instances. Li et al. [4], proposed a mathematical model of integrated process planning and scheduling, an evolutionary algorithm-based approach to facilitate the integration and optimization of these two functions. To improve the optimized performance of their proposed approach, efficient genetic representation and operator schemes are developed. Majoji et al. [8], presented the application of fuzzy set theory (FST) within the context of integrated planning and scheduling. They demonstrate that the application of FST in dealing with qualitative features of plant personnel and plant requirements are necessary in order to maximize plant performance, with respect to the financial aspects. The FST output can be integrated into a formulation to determine the optimal allocation of operators in different plants. The second part of these series presents the impact of personnel allocation on the overall integrated planning and scheduling framework. Lin et al. [7], assessed an integrated production planning (IPP) for the steelworks continuous casting-hot rolling (SCC-HR) process in the steel industry. They introduced a new concept named order-set model to deal with the difficulty of large-scale decision variables. In addition, they developed a multi-objective optimization model with interval-valued objective functions in order to optimize the throughput of each process, the hot charge ratio of slabs, the utilization rate of tundishes and the additional cost of technical operations considering the multiple objectives and uncertainties of the given IPP problem. Furthermore, they proposed a new approach based on a modified interval multi-objective optimization evolutionary algorithm (MI-MOEA) to solve the problem. They revealed that their proposed method generates quite effective and practical solutions within a short time and is developed and implemented together with an IPP system based on the IPP model and MI-MOEA.

As reviewed in the available literature, although several frequently-used meta-heuristics are adopted for solving IPPS problem, a proper IPPS problem model that is consistent with more qualified aspect of job shop process planning and scheduling problems is yet to be proposed. There is still demand for fuzzy approaches to deal with the required data that are achieved by judgment. Hence, in this article, the main focus is on analyzing some qualitative parameters in terms of their impact on
the choice of the IPPS problem. Here, the Mamdani FIS is adopted for considering these qualitative parameters together with the IPPS problem.

3. Methodology. Synchronized optimization of the process planning and scheduling will be implemented through an integrated approach based on FIS, CP and SA algorithms.

3.1. Qualitative parameters affecting the process plan. Process planning and scheduling have an important role in the efficiency of the workshop production system, in a simultaneous manner. Effective variables in operations sequence on existing machines (given fixed layout) should be identified and controlled carefully to achieve an appropriate process plan. Process designers apply the fuzzy logic approach to deal with the complexity and ambiguous nature of some of these variables.

Based on fuzzy logic, to assess the utility of a process plan, determining linguistic variables is necessary to measure effective qualitative parameters thereof, Akgun et al. [1]. Utility can be measured through parameters like: ease in setup, adaptation among machines, distance between the installed machines and ease in material displacement in operations run on different machines. These parameters are tabulated in Tables 1 with membership function of corresponding verbal terms as the input of the FIS. Required qualitative parameters are assessed through some experts and observers in a workshop system (given fixed layout), through approximate reasoning. The outputs of the FIS consist of ease in material flow and production, are tabulated in Tables 2.

3.2. Model design. The attempt to reduce costs or the flow time in a workshop system leads to facilitation of the production and marketing objectives, etc. In this context, the objective is to integrate the process planning and scheduling and introduce the affective qualitative parameters with respect to the implementation of operations sequencing. Optimization of process planning through a fuzzy approach is the other objective here. The techniques applied in this newly proposed model, are illustrated in Fig. (1).

In order to facilitate systematic computation of the utility in the administrative structure of the meta-heuristic approach, it is necessary to consider the combination of experts’ knowledge and monitoring the system in a fuzzy knowledge base in this approach.

First, given fixed layout, affecting factors related to operations sequence on machines are specified as the Input variables that affect the operations sequence utility. In this study, the following four parameters are of concern: ease in setup, adaptation among machines, distance between machines, ease in material displacement in different machines. Afterwards quantities of each one of the parameters regarding the relations among machines are determined based on fuzzy membership function. Accordingly, the weight of each parameter is obtained for these relations.

The next step is to resort to the related database to retrieve, information on the machines (including machine number, size and distance between machines, etc.) and to the fuzzy variables database to retrieve the membership function to the quantities, weight of the parameters and linguistic terms of output variable.

The linguistic values for ranking the output variables include: Absolute (A), very important (E), important (I), normal (O), unimportant (U) and poor (X). The
Table 1. Inputs of fuzzy inference systems

| Membership Functions of inputs | Input: Ease in setup |
|--------------------------------|----------------------|
| FIS Variables                  |                      |
| Setup                          |                      |
| Production                     |                      |
| Compatibility                  |                      |

| Input: Adaptation among machines |
|----------------------------------|

| Input: Distance between the installed machines |
|-----------------------------------------------|

| Input: Ease in material displacement in different machines |
|-----------------------------------------------------------|

knowledge base is determined by expert opinion which includes fuzzy rules (the IF-THEN rules) for all parameters relations. After obtaining the fuzzy variables and configuring the knowledge base, it is necessary to apply inference engine.
The inference engine converts fuzzy inputs in IF-THEN rules from the knowledge base to proper Fuzzy output. In the Mamdani method, the input variables consist of: Amount and weight of parameters for existing relations and the output consist of the closeness rate regarding certain operations of the installed machines, per relation. For each one of the parameters in any respect final membership function rate is achieved in relation to closeness rates in two machines, consequently, the fuzzy output will become to a certain value through centroid defuzzification method, the average absolute value of which is determined as the final value of closeness rates for allocated operations based on the machine, and is ready to be applied in the meta-heuristic algorithm of SA and CP models. The CP model here is edited through the Optimization Programming Language (OPL) and is formulated through IBM ILOG CP Optimizer. Data structures in OPL can be constructed through tuples that cluster closely related data.

The SA algorithm of each one of iterations is assessed based on permutation of the operations sequence of different parts on the machine. After the operations run on the sequence of the given machines, iteration and closeness rates are achieved. The utility of each process plan is calculated by summation of the closeness rate in each sequence.

The second objective is to model the necessary flexibility in workshop system, that include flexibility of tools, machine, process and sequence in the form of objective function to minimize the total cost of supply flexibility. Production costs consist of the cost of machine use, tools, machine and tool Switchover and set up.
In this context, the prerequisites for processing part in the form of restrictions are defined as processing operations priorities. Mathematical equations related to the objective function in this section are defined in Lian et al. [6].

The third objective of meta-heuristic algorithms is the determination of the best operation sequence and the determination of their best process plan in a simultaneous manner. Optimized sequence of orders will in minimizing the average of completion time of existing orders in production system. The purpose of this function is based on the mathematical equations defined in Li et al. [5]. To solve this problem, objective functions are defined as a goal programming model which would minimize the sum of adverse deviations of each objective from its goals. The goals are defined for each one of the objectives as \((G_{TWC}, G_{MakeSpan}, G_U)\) and they become an ideal restriction which is then added to the objective function. The limits of the system, including prerequisite relations in operations sequence are run in MATLAB program by a defined function.

The total cost of the obtained flexibility is calculated through Eq. (2) and the results are tabulated in Table 3. The completion time is calculated through Eq. (3). The ultimate utility of each process plan is calculated through Eq. (4). The objective function can be formulated to minimize the sum of deviation from the goals in the model, Eqs. (5-8). The weighted sum of deviation of objective functions goals is obtained through Eq. (1).

\(w_1, w_2 \) and \(w_3\) are the weights related to each of the objective function, which are determined through the relevant experts with the importance of these objectives.
Table 3. The Goal Programming Formulation of the IPPS Problem

**Parameters**
- \( p \): Part indicator, \( p = 1, \ldots, PNo \)
- \( O^p \): The set indicating operations of \( p^{th} \) part
- \( i \): Operation indicator, \( i \in O^p, p = 1, \ldots, PNo \)
- \( d \): TAD indicator
- \( t \): Tool indicator
- \( m \): Machine indicator

**Machine** \( i \): The set indicating machine candidates of the \( i^{th} \) operation

**TAD** \( i \): The set indicating TAD candidates of the \( i^{th} \) operation

**Tool** \( i \): The set indicating tool candidates of the \( i^{th} \) operation

**MC** \( m \): The cost of using \( m^{th} \) machine per operation

**TC** \( t \): The cost of using \( i^{th} \) tool per operation

**MFE** \( m_k^m l \): The rate of Material Flow Ease between machines \( m_k \) and \( m_l \)

**PE** \( m_k^m l \): The rate of Production Ease between machines \( m_k \) and \( m_l \)

**Decision Variables**

\[
\text{operation}_{imtd}^p = \begin{cases} 
1 & \text{If the } i^{th} \text{ operation of part } p \text{ is done in } m^{th} \text{ machine with } t^{th} \text{ tool and } d^{th} \text{ TAD} \\
0 & \text{Otherwise}
\end{cases}
\]

\[
\text{part}_{ij}^p = \begin{cases} 
1 & \text{If the } j^{th} \text{ operation of part } p \text{ is done immediately after the } i^{th} \text{ operation of part } p \\
0 & \text{Otherwise}
\end{cases}
\]

\[
\text{time}_i^p = \text{Cumulative time of operations of part } p \text{ completed until the completion of the } i^{th} \text{ operation}
\]

\( OM_i = \text{The } i^{th} \text{ operation machine, } OM_i \in \text{Machine}_i \)

\( OT_i = \text{The } i^{th} \text{ operation TAD}, OT_i \in \text{TAD}_i \)

**Proposed Goal Programming Model:**

\[
\begin{align*}
\text{Min } D &= \left( w_1 \times \frac{d_1}{G_{TWC}} \right) + \left( w_2 \times \frac{d_2}{G_{MakeSpan}} \right) + \left( w_3 \times \frac{d_3}{G_U} \right) \quad (1) \\
\text{Subject to : } & \\
TWC &= \sum_{i \in O^p} \sum_{m \in \text{Machine}_i} \sum_{t \in \text{Tool}_i} \sum_{d \in \text{TAD}_i} \text{operation}_{imtd}^p (MC_{OM_i} + TC_{OT_i}) \quad (2) \\
MakeSpan &= \max_{p=1, \ldots, PNo} (\text{time}_i^p) \quad (3) \\
U &= \sum_{p=1}^{PNo} \sum_{i,j \in O^p} \text{part}_{ij}^p (MFE_{OM_i,OM_j} + PE_{OM_i,OM_j}) \quad (4) \\
TWC - d_1^- &\leq G_{TWC} \quad (5) \\
MakeSpan - d_2^- &\leq G_{MakeSpan} \quad (6) \\
U + d_3^+ &\geq G_U \quad (7) \\
d_1^-, d_2^-, d_3^+ &\geq 0 \quad (8)
\end{align*}
\]
After the formulating the problem with CP and SA algorithm, the results will be compared.

4. Application of the proposed method. Sources specifications consisting of application cost of each operational unit together with time switching tool, switching machine and change in settings are tabulated in Table 4.

### Table 4. Sources Specifications

| The cost per operation (MC) | Symbol | Source               |
|-----------------------------|--------|----------------------|
| 50                          | M1     | CNC milling machine 1|
| 60                          | M2     | CNC milling machine 2|
| 30                          | M3     | Grinding CNC machine |
| 35                          | M4     | Column drilling equipment |
| 20                          | M5     | Hand drilling equipment |
| 20                          | M6     | Grinding machine     |

| The cost per operation (TC) | Symbol | Resource         |
|-----------------------------|--------|------------------|
| 6                           | T1     | Drill 1          |
| 5                           | T2     | Drill 2          |
| 10                          | T3     | Drill 3          |
| 15                          | T4     | Drill 4          |
| 13                          | T5     | Drill 5          |
| 14                          | T6     | Drill 6          |
| 8                           | T7     | Drill 7          |
| 10                          | T8     | Drill 8          |
| 5                           | T9     | Drill 9          |
| 10                          | T10    | Polishers        |
| 15                          | T11    | Reamer 1         |
| 20                          | T12    | Reamer 2         |
| 18                          | T13    | Reamer 3         |
| 15                          | T14    | Diamond blades   |
| 18                          | T15    | Milling plate    |
| 13                          | T16    | Spark            |
| 24                          | T17    | Magnetic stone   |

The three parts specifications provided in Tables 5 through 10, are considered as inputs for the IPPS. The first part has 11, the second part has 9 and the third has 8 Features.

Influencing qualitative parameters include ease in setup, adaptation among machines and ease in material displacement in different machines. Membership function to calculate the utility of each process plan based on the processing sequence
of each part for each parameter is defined as a fuzzy triangle number, with parameters range of [0,30] for distance among machines and [0,5] for all other parameters. Finally, for calculating the closeness rate of certain operations related to given machines, the IF-THEN rules are defined for each one of the parameters in each relation and weight of each parameter. Rules and results of the FIS based on distance and
Table 7. Technical Specifications of Part 3

| Features | Index | operation | TAD candidate | Machine candidate | Tool candidate | Machining time for each candidate machine (s) |
|----------|-------|-----------|---------------|-------------------|---------------|-----------------------------------------------|
| F₁       | oper₁ | Milling   | -Y,-X         | M₁₅,M₂          | T₁₄₅,T₁₅₆₇₁₇ | 30, 35                                        |
| F₂       | oper₂ | Milling   | +Z,+X         | M₁₂,M₂          | T₁₄₅,T₁₅₆₇₁₇ | 28, 30                                        |
| F₃       | oper₃ | Milling   | +Z,+Y         | M₁₃,M₂          | T₁₄₅,T₁₅₆₇₁₇ | 33, 30                                        |
| F₄       | oper₄ | Milling   | +X,-X         | M₁₄,M₂          | T₁₄₅,T₁₅₆₇₁₇ | 29, 25                                        |
| F₅       | oper₅ | Milling   | +X,-X         | M₁₅,M₂          | T₁₄₅,T₁₅₆₇₁₇ | 37, 31                                        |
| F₆       | oper₆ | Drilling  | -Z,+Z         | M₁₆₃,M₄₅       | T₉            | 50, 60, 40                                    |
| F₇       | oper₇ | Milling   | -Z            | M₁₇,M₂          | T₁₄₅₆₇₁₇₁₇   | 40, 39                                        |
| F₈       | oper₈ | Drilling  | -Z            | M₁₈₉₅₆₅       | T₈            | 39, 50, 38                                    |

Table 8. Precedence Relations of Part 1

Precedence relations

Oper₁ is first operation.
Oper₂ is prior to Oper₄, Oper₅, Oper₁₁ and Oper₁₂.
Oper₃ is prior to Oper₄, Oper₅ and Oper₁₀.
Oper₅ is prior to Oper₇, Oper₁₁ and Oper₁₂.
Oper₆ is prior to Oper₁₃.
Oper₇ is prior to Oper₁₃.
Oper₁₁ is prior to Oper₁₂.

Table 9. Precedence Relations of Part 2

Precedence relations

Oper₁ is first operation.
Oper₂ is prior to Oper₇, Oper₉.
Oper₃ is prior to Oper₅, Oper₉.
Oper₄ is prior to Oper₅, Oper₆.
Oper₅ is prior to Oper₆.
Oper₇ is prior to Oper₈, Oper₁₀.
Oper₉ is prior to Oper₁₀.

Table 10. Precedence Relations of Part 3

Precedence relations

Oper₁ is first operation.
Oper₂ is prior to Oper₆, Oper₅.
Oper₃ is prior to Oper₄, Oper₅.
Oper₄ is prior to Oper₅, Oper₆.
Oper₅ is prior to Oper₆.
Oper₇ is prior to Oper₈.
ease in transportation (Material Flow FIS), the closeness distance among machines based on ease in material flow as the output of the FIS on the distance, and the replacement parameters tabulated in Tables 11 and 12, and Fig. (2).

Table 11. Rules of Material Flow FIS on Distance and Transportation Ease Parameters

| Distance between installed machines | Ease in material displacement in different machines |
|------------------------------------|-----------------------------------------------|
| VH                                 | L     | M     | H     | VH    |
| H                                  | X     | X     | U     | U     |
| M                                  | U     | U     | O     | O     |
| L                                  | U     | O     | I     | E     |
| VL                                 | U     | O     | I     | A     |

Figure 2. Structure of the Material Flow FIS

Table 12. Score of Pair Machines Based on Material Flow FIS

| Ease in material flow | M1  | M2  | M3  | M4  | M5  | M6  |
|-----------------------|-----|-----|-----|-----|-----|-----|
| M1                    | 5.69| 2.74| 5.69| 2.00| 1.50| 1.50|
| M2                    | 3.74| 5.69| 2.56| 3.00| 4.37| 1.50|
| M3                    | 4.50| 4.37| 5.69| 1.20| 0.37| 1.50|
| M4                    | 1.50| 1.50| 1.20| 5.69| 2.50| 1.20|
| M5                    | 1.20| 2.56| 1.50| 1.50| 5.69| 2.56|
| M6                    | 1.50| 2.00| 1.50| 1.20| 3.56| 5.69|

Rules and results of the FIS based on ease in setup and adaptation among machines (Ease in production FIS) are shown in Tables 13 and 14, and Fig. (3).
In this article, the objective is to find the appropriate and possible process plan including operations sequencing of part processing, tools and (TAD) for each operation, timing allocation and operations sequencing based on the machines. Cost and make-span objectives minimize the cost and time for processing the parts; the utility function maximizes process plan utility in terms of qualitative parameters of distance, ease in setup, adaptation among machines and ease in material displacement through FIS. The goal programming approach is applied here to solve the multi-objective problem. The goal index of each objective is determined by solving the single objective problem with respect to each objective and the objective weights are determined according to expert opinion expressed in Table 15.
### Table 15. Goals and Weights of Objectives

| Objective Function | Goal | Weight |
|-------------------|------|--------|
| TWC               | 1484 | 1      |
| Make Span         | 468  | 2      |
| Utility           | 288.24 | 3     |

4.1. **Applying SA algorithm in solving the IPPS problem.** The Simulated Annealing (SA) algorithm is a stochastic meta-heuristic algorithm used to solve complex and combinatorial optimization problems which was introduced by Kirkpatrick et al. [3]. SA is originated by an analogy to the statistical mechanics of annealing in solids, in which a crystalline solid is heated and then allowed to cool very slowly until it achieves its most regular possible crystal lattice configuration (its minimum lattice energy state), and thus is free of crystal defects. SA establishes the connection between this type of thermodynamic behavior and the search for global minima for a discrete optimization problem. The basic requirement for simulating this process is the ability to simulate how the system reaches thermodynamic equilibrium at each fixed temperature in the schedule of decreasing temperatures that is used to anneal it.

The key algorithmic feature of SA is in providing the means to avoid local optima by allowing hill-climbing moves. As the temperature parameter is decreased to zero, hill-climbing moves occur less frequently, and the solution distribution associated with the inhomogeneous Markov chain, which models the behavior of the algorithm, converges to a form where all the probability is concentrated on the set of global optimal. To solve the problem through SA algorithm, its parameters are first determined through the involved various problems, Table 16.

### Table 16. The Parameters of SA Algorithm

| Parameters               |            |
|-------------------------|------------|
| The number of initial population = 20 | The iterations time = 300s |
| The number of neighborhood = 10 | Alpha = 0.99 |

4.1.1. **Steps applied in this context.**

**Step 1.** Set the algorithm parameters. The iteration time for termination here is considered as 300 (StTime = 300) seconds, allowing for a comparison to be run with CP model. Then, set the initial temperature at $T_0$, and the temperature damping rate at $\alpha$ and $Iter = 1$.

**Step 2.** Generate the initial solution $X$ which generally includes a permutation of $n$ tasks so, the length of the solution is $v = n$. For the initial solution, choose random permutation of position in $v$ and make it feasible by considering the precedence relations. Each position is related to one operation in each part. All positions are tabulated in Table 17 as a list.

Here, random numbers are produced to assign each task to its candidates for machines, tools and TADs. Next, the permutation solution is scheduled in a feasible manner by considering the machine assignments and the size of the tasks. Then the multi-objective function that includes total cost, make-span and the ultimate
Table 17. The optional list of Positions of Operations of Parts

| Position | Parts | Operations |
|----------|-------|------------|
| 1        | 1     | 1          |
| 2        | 1     | 2          |
| 3        | 1     | 3          |
| 4        | 1     | 4          |
| 5        | 1     | 5          |
| 6        | 1     | 6          |
| 7        | 1     | 7          |
| 8        | 1     | 8          |
| 9        | 1     | 9          |
| 10       | 1     | 10         |
| 11       | 1     | 11         |
| 12       | 1     | 12         |
| 13       | 1     | 13         |
| 14       | 2     | 1          |
| 15       | 2     | 2          |
| 16       | 2     | 3          |

| Position | Parts | Operations |
|----------|-------|------------|
| 17       | 2     | 4          |
| 18       | 2     | 5          |
| 19       | 2     | 6          |
| 20       | 2     | 7          |
| 21       | 2     | 8          |
| 22       | 2     | 9          |
| 23       | 2     | 10         |
| 24       | 3     | 1          |
| 25       | 3     | 2          |
| 26       | 3     | 3          |
| 27       | 3     | 4          |
| 28       | 3     | 5          |
| 29       | 3     | 6          |
| 30       | 3     | 7          |
| 31       | 3     | 8          |

processes utility are formulated. For example, the solution of the problem with 31 tasks \(v = 31\) and six machines \(MN_o = 6\) is presented as the Table 18.

**Step 3.** Until \(Time \leq StTime\), repeat steps 3.1 to 3.3:

**Step3.1.** Modify the assignment by generating a new solution in \(X'\) neighborhood and apply one of the procedures (e.g. swap, insertion and reversion), in a random manner.

**Step3.2.** Evaluate the fitness function of \(X'\) and if \(Z(X') \leq Z(X)\), then \(X'\) is a better option, it is accepted, thus \(X = X'\). If not, compute \(\Delta = Z(X') - Z(X)\), and select a random number \((rand \sim (1, 0))\). If \(e^{-\frac{\Delta}{T}} \geq rand\) then put \(X = X'\).

**Step3.3.** Lower the temperature \((T = T \times \alpha)\), \(Iter = Iter + 1\) and go to the step 3.

**Step 4.** Report the obtained solution as the best solution \((X^*)\) and stop the operation.

The flowchart of implantation of the presented problem with SA algorithm is shown in Fig. (4). The pseudo code of the SA algorithm applied in this study is presented in Fig. (5).

4.2. **Applying CP method in solving the IPPS problem.** The main contribution of this section is to assess the problem by applying CP method. For this purpose, the problem is cast as an OPL model designed for the IBM ILOG CP OPTIMIZER which models the system design, executing platform, and performance requirements [2]. OPL is a modeling language for combinatorial optimization, designed to simplify optimization problems in a substantial manner. OPL increases the applicability of modeling languages by applying techniques from CP.
### Table 18. Solution of SA algorithm

| Random Position | Feasible Position | Parts | Operations | Machines | Tools | TAD |
|-----------------|-------------------|-------|------------|----------|-------|-----|
| 17              | 14                | 2     | 1          | 2        | 14    | -Z  |
| 5               | 17                | 2     | 4          | 1        | 15    | Z   |
| 3               | 16                | 2     | 3          | 2        | 16    | -Y  |
| 10              | 18                | 2     | 5          | 1        | 16    | -Z  |
| 2               | 19                | 2     | 6          | 6        | 10    | Y   |
| 31              | 15                | 2     | 2          | 4        | 1     | -Z  |
| 12              | 20                | 2     | 7          | 4        | 11    | -Z  |
| 19              | 21                | 2     | 8          | 2        | 16    | -Z  |
| 9               | 23                | 2     | 10         | 4        | 2     | X   |
| 27              | 24                | 3     | 1          | 5        | 3     | -X  |
| 21              | 26                | 3     | 3          | 3        | 4     | Y   |
| 18              | 30                | 3     | 7          | 5        | 12    | Y   |
| 14              | 31                | 3     | 8          | 6        | 10    | A   |
| 6               | 25                | 3     | 2          | 2        | 15    | -Y  |
| 13              | 27                | 3     | 4          | 1        | 17    | Z   |
| 4               | 28                | 3     | 5          | 2        | 15    | -Y  |
| 26              | 29                | 3     | 6          | 3        | 4     | Y   |
| 30              | 22                | 2     | 9          | 4        | 5     | X   |
| 7               | 1                 | 1     | 1          | 5        | 13    | X   |
| 20              | 3                 | 1     | 3          | 4        | 6     | -Y  |
| 16              | 10                | 1     | 10         | 2        | 17    | -Z  |
| 28              | 2                 | 1     | 2          | 1        | 16    | A   |
| 8               | 5                 | 1     | 5          | 6        | 10    | -X  |
| 25              | 9                 | 1     | 9          | 2        | 15    | -Y  |
| 23              | 6                 | 1     | 6          | 2        | 14    | X   |
| 29              | 4                 | 1     | 4          | 2        | 17    | Z   |
| 15              | 7                 | 1     | 7          | 2        | 17    | X   |
| 24              | 8                 | 1     | 8          | 2        | 16    | X   |
| 22              | 13                | 1     | 13         | 3        | 9     | Z   |
| 1               | 11                | 1     | 11         | 2        | 14    | -Z  |
| 11              | 12                | 1     | 12         | 5        | 8     | -Z  |

#### 4.2.1. Variables.
Data structures in OPL can be constructed through tuples which cluster related data. In this model, a tuple is applied to define inputs as follows.

\[
\text{Tasks} = \{ \langle \text{ID}, \text{PartNo}, \text{OperationNo}, \{\text{TADNo}\}, \{\text{ToolNo}\},
\{\text{MachineNo}\}, \{\text{pTime}\}, \{\text{Succs}\} \rangle \}
\]

Description of the Tasks are expressed in Table 19.

In this CP model, two types of variables are needed, the interval variable and interval sequence variable. The interval variable represents an interval of time of a task process the scheduling problem states of which are unknown. An interval is characterized by a starting value, an ending value, a size and a magnitude. The length of an interval is its ending time minus its beginning time. Some functions are developed to retrieve the interval variable properties. For example, for an interval variable, four functions, startOf (a), endOf (a), lengthOf (a), and presenceOf (a),
are applied to retrieve the start time of a, the completion time of a, the duration time of performing a, and the last is a Boolean function which indicates whether a is absent or present, respectively [10]. An important additional characterization of interval variables is the fact that they can be optional; that is, one can decide not to consider them in the solution schedule. In this study, a job can be done on a set of machines, therefore optional interval variables are applied to model this case. The term tasks, is defined as an interval variable which represents the $i^{th}$ task ($i \in Tasks$). Due to the flexible nature of operations another interval must be defined which would meet this need. For this purpose the Modes tuple derived

**Figure 4.** The Flowchart of SA Algorithm
Set algorithm parameters (): \( T \leftarrow T_0 \), \( \text{Iter} = 1 \), \( \alpha \leftarrow \alpha_0 \)

Generate initial (feasible) assignment, \( X \) (assign n jobs to m machines)

while \( \text{Time} \leq \text{StTime} \)

\[ \text{Modify assignment by generating neighborhood solution } X' \text{ of } X. \]

Calculate objective function

Let \( \Delta \leftarrow Z(X') - Z(X) \)

if \( \Delta < 0 \) then \( X \leftarrow X' \)

else generate a random number \( r \)

\[ \text{if } r \leq \exp \left( -\frac{\Delta}{T} \right) \text{ then } X \leftarrow X' \text{ endif} \]

endif

Reduce Temperature \( T \)

\( \text{Iter} \leftarrow \text{Iter} + 1 \)

endwhile

\( X^* \leftarrow \text{best}(X) \)

Return \( X^* \)

**Figure 5.** Pseudo-Code of SA Algorithm

**Table 19.** Description of the *Tasks*

| ID       | Exclusive number of each member of the tuples |
|----------|-----------------------------------------------|
| PartNo   | The number of the parts                       |
| OperationNo | The number of operations necessary for part processing |
| \{TADNo\} | The set of TAD candidates                     |
| \{ToolNo\} | The set of tool candidates                    |
| \{MachineNo\} | The set of machine candidates               |
| \{pTime\}  | The set of Machining time for each candidate machine (s) |
| \{Succs\}  | The set of successor operations               |

from *Tasks* are defined as follows.

\[ \text{Modes} = \{< \text{Task}, \text{PartNo}, \text{OperationNo}, \text{TADNo}, \text{ToolNo}, \text{MachineNo}, \text{pTime} >\} \]

Description of the *are* expressed in Table 20.

The mode, is defined as an interval variable which represents the \( j \)\(^{th} \) mode of a task \( (j \in \text{Modes}) \) with \( j \cdot \text{pTime} \). The interval sequence variable represents a total order over a set of interval variables. A non-negative integer (the type) can be associated with each interval variable in the sequence. In this proposed model, there exist some machines which can be mapped as sequences, consequently, \( \text{machine}_m \) is defined as an interval sequence variable which represents the \( m \)\(^{th} \) machine \( (m \in 1, ..., M\text{No}) \). Furthermore, we define another interval sequence variable as \( \text{part}_p \) is defined which represents the \( p \)\(^{th} \) part \( (m \in 1, ..., P\text{No}) \).
Table 20. Description of the Modes

| task | A tuple type data represent the Task which the Mode is derived from |
| PartNo | Indicates the number of the parts which equal to task.Part.No |
| OperationNo | Indicates the number of the operations in one part which equals to task.Operation.No |
| TADNo | Indicates the number of TADs which is a member of task.\{TAD.No\} |
| ToolNo | Indicates the number of tools which are the members of task.\{Tool.No\} |
| MachineNo | Indicates the number of machines which are a member of task.\{Machine.No\} |
| pTime | Indicates the machining time for MachineMachine.No |

4.2.2. Constraints. As described in sub-section 3.2, the objective function can be formulated to minimize the poor distortion harmonic summation \((w_id_i)\) of model related goals. Therefore, the first three constraints are defined as following statements:

\[
TWC - d_1 \leq GTWC \\
MakeSpan - d_2 \leq GMakeSpan \\
U + d_3^+ \geq GU
\]

OPL has some predefined constraints indicating the flexibility of the CP model. One of them is alternative which is applied in modeling the selection of one or more intervals from a set of optional intervals. This alternative is applied in interval variables as follows:

\[
\text{alternative}(\text{task}_i, \text{mode}_j), \ \forall \ i \in \text{Tasks}, \ j \in \text{Modes}|i.ID == j.i.ID.
\]

This constraint assures that only one mode of the task\(_i\) in performed on the machines.

Another predefined constraint is noOverlap which is applied to assure that there exists no overlap between any two tasks. This constraint states that the sequence defines a chain of non-overlapping interval, where any intervals in the chain is constrained to end before beginning of the next interval in the chain. This interval sequence is applied in variables as follows:

\[
\text{noOverlap}(\text{machine}_m), \ \forall \ m \in 1, \ldots, \text{MNo}
\]

This constraint is applied to remove any overlap between any two tasks on a single machine.

\[
\text{noOverlap}(\text{part}_p), \ \forall \ p \in 1, \ldots, \text{PNo}
\]

This constraint is applied to remove any overlaps between any two tasks in a single part.

Another predefined constraint which is applied to restrict the relative positions of interval variables is endBeforeStart. This constraint is applied in interval variables
as follows:

\[ \text{endBeforeStart}(task_i, task_j), \ \forall i \in \text{Tasks}, \ j \in \{i.\text{Succs}\} \]

This constraint assures that the tasks placed in the successive set beginning after the prior task is ended.

4.2.3. Multi-Objectives. The multi-objective function is formulated through properties of the interval variables in three parts as follows:

Part 1: Objective function to minimize the total equivalent costs of machines and tool uses:

\[ TWC = \sum_{p \in \text{Modes}} \text{presenceOf}(mod_{mp}) \times (MC(p.\text{MachineNO}) + TC(p.\text{ToolNO})) \]

Part 2: Objective function to minimize the completion time:

\[ \text{MakeSpan} = \min_{i \in \text{Tasks}} (\text{endOf}(task_i)) \]

Part 3: Objective function to maximize the ultimate processes utility:

\[ U = \sum_{p=1}^{PNo} \sum_{i \in \text{Modes}} \left( \text{MFE}(i.\text{MachineNo}, \text{typeOfNext}(part_p, mode_i)) + \text{PE}(i.\text{MachineNo}, \text{typeOfNext}(part_p, mode_i)) \right) \]

The \text{typeOfNext} is an OPL function that represents the type of the next interval in a given sequence. In this proposed model, this function is altered in a manner that it represents the number of the next interval in a given machine, \text{Number Of Next}.

Finally, the overall objective is defined as follows:

\[ \min D = \left( w_1 \times \frac{d_1^+}{G_{TWC}} \right) + \left( w_2 \times \frac{d_2^-}{G_{\text{MakeSpan}}} \right) + \left( w_3 \times \frac{d_3^+}{G_U} \right) \]

5. Computational results. The final solution of SA algorithm is shown in Figs. (6) and (7). The Gant chart in Fig. (9) shows the operations sequence of parts in the best solution of SA algorithm. The Gant chart in Fig. (7) displays the operations sequence on machines in the best solution of SA algorithm.

The final value of objective functions which include total cost, completion time and the ultimate processes utility consist of \( z_1 = 87.30202 \), \( z_2 = 1669 \) and \( z_3 = 493 \).

The final solution of problem by solving multi-objective model through CP is shown in Figs. (8) and (9). The operations sequence of parts in the solutions of CP is shown in the Fig. (8), and the operations sequence on machines in the solution of CP are shown in the Fig. (9). The value of the objective function consist of \( z_1 = 258.3761 \), \( z_2 = 1514 \) and \( z_3 = 478 \).

6. Discussion and conclusion. The integration of process planning and scheduling in a workshop system is considered as the major domains in this study, by considering the qualitative aspects of the process planning through the FIS. As reviewed in the available literature, although several frequently-used meta-heuristics are adopted for solving IPPS problem, a proper IPPS problem model that is consistent with more qualified aspect of job shop process planning and scheduling problems is yet to be proposed.
The goals and completion times of CP method and SA algorithm are tabulated in Table 23.

A multi-objective model is proposed here to incorporate constructive meta-heuristics to solve an IPPS problem where qualitative parameters affecting the orders sequencing are considered and assessed through the FIS. The purpose of

| Part | Operation | Machine | TAD | Tool | Start Time | Machining Time | Finish Time |
|------|-----------|---------|-----|------|------------|----------------|-------------|
| 1    | 1         | 2       | -3  | 16   | 0          | 38             | 38          |
| 1    | 2         | 1       | -3  | 14   | 100        | 37             | 137         |
| 1    | 3         | 1       | -3  | 14   | 59         | 41             | 100         |
| 1    | 4         | 1       | 2   | 16   | 323        | 31             | 354         |
| 1    | 5         | 6       | -2  | 10   | 394        | 40             | 434         |
| 1    | 6         | 5       | -3  | 1    | 139        | 30             | 169         |
| 1    | 7         | 3       | -3  | 11   | 169        | 40             | 209         |
| 1    | 8         | 1       | -3  | 16   | 269        | 54             | 323         |
| 1    | 9         | 5       | 1   | 2    | 38         | 21             | 59          |
| 1    | 10        | 5       | 1   | 3    | 354        | 40             | 394         |
| 1    | 11        | 5       | 2   | 4    | 290        | 30             | 239         |
| 1    | 12        | 5       | 2   | 12   | 239        | 30             | 269         |
| 1    | 13        | 6       | 4   | 10   | 434        | 50             | 484         |
| 2    | 1         | 2       | -2  | 16   | 38         | 20             | 58          |
| 2    | 2         | 2       | 3   | 15   | 82         | 29             | 111         |
| 2    | 3         | 2       | -3  | 16   | 58         | 24             | 82          |
| 2    | 4         | 4       | -1  | 4    | 269        | 66             | 335         |
| 2    | 5         | 4       | 1   | 5    | 335        | 59             | 394         |
| 2    | 6         | 5       | 1   | 13   | 394        | 41             | 435         |
| 2    | 7         | 5       | -2  | 6    | 111        | 28             | 139         |
| 2    | 8         | 2       | 3   | 14   | 180        | 49             | 229         |
| 2    | 9         | 2       | 4   | 16   | 139        | 41             | 180         |
| 2    | 10        | 6       | 1   | 10   | 229        | 40             | 269         |
| 3    | 1         | 1       | -2  | 14   | 0          | 30             | 30          |
| 3    | 2         | 2       | 3   | 14   | 298        | 30             | 328         |
| 3    | 3         | 2       | 3   | 14   | 229        | 30             | 259         |
| 3    | 4         | 1       | -1  | 17   | 354        | 29             | 383         |
| 3    | 5         | 2       | 1   | 14   | 383        | 31             | 414         |
| 3    | 6         | 5       | -3  | 9    | 453        | 40             | 493         |
| 3    | 7         | 2       | -3  | 15   | 259        | 39             | 298         |
| 3    | 8         | 3       | -3  | 8    | 414        | 39             | 453         |
Figure 6. Parts Operations Sequence in SA solution

Figure 7. Machines Operations Sequence in SA solution

Process planning here is to find optimal plan for processing of parts in parallel with minimizing cost and maximizing utility rate. Furthermore, scheduling intends to minimize the total completion time of available parts, design a model discussed for solving multi-objective problem, and integrated scheduling and process planning. The objectives include minimizing operational costs, minimizing total time and maximizing ultimate processes utility rate. The problem is solved through SA and CP algorithms. The results obtained through CP outperform SA algorithm. In comparison with previous assessments run in the field of IPPS where the functional multi-objective criteria like cost, time, and utility are of less concern, the qualitative parameters affecting process planning based on fuzzy Knowledge are proposed in this study which open a new window in this domain.

The interesting future directions for IPPS problem can be developing the other meta-heuristic algorithms and considering other costs such as machine, tools and TADs change costs.
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Table 22. The Best Solution obtained through CP

| Part | Operation | Machine | TAD | Tool | Start Time | Machining Time | Finish Time |
|------|-----------|---------|-----|------|------------|---------------|-------------|
| 1    | 1         | 2       | -3  | 16   | 0          | 38            | 38          |
| 1    | 2         | 2       | -3  | 16   | 38         | 37            | 75          |
| 1    | 3         | 1       | -3  | 16   | 75         | 41            | 116         |
| 1    | 8         | 1       | -3  | 16   | 116        | 52            | 168         |
| 1    | 10        | 3       | 1   | 3    | 168        | 40            | 208         |
| 1    | 6         | 5       | -3  | 1    | 208        | 30            | 238         |
| 1    | 9         | 5       | -1  | 2    | 238        | 20            | 258         |
| 1    | 11        | 5       | 2   | 4    | 258        | 30            | 288         |
| 1    | 7         | 5       | -3  | 11   | 288        | 30            | 318         |
| 1    | 13        | 6       | 4   | 10   | 318        | 50            | 368         |
| 1    | 5         | 6       | 2   | 10   | 368        | 40            | 408         |
| 1    | 12        | 5       | 2   | 12   | 408        | 30            | 438         |
| 1    | 4         | 1       | -3  | 16   | 438        | 30            | 468         |
| 2    | 1         | 1       | -2  | 16   | 0          | 20            | 20          |
| 2    | 3         | 1       | -3  | 16   | 20         | 24            | 44          |
| 2    | 2         | 1       | 3   | 16   | 44         | 29            | 73          |
| 2    | 4         | 5       | 3   | 4    | 73         | 51            | 124         |
| 2    | 5         | 5       | 1   | 5    | 124        | 38            | 162         |
| 2    | 6         | 5       | 1   | 13   | 162        | 41            | 203         |
| 2    | 7         | 5       | 2   | 6    | 318        | 28            | 346         |
| 2    | 8         | 1       | -3  | 16   | 351        | 47            | 398         |
| 2    | 9         | 1       | 4   | 16   | 398        | 40            | 438         |
| 2    | 10        | 6       | 1   | 10   | 438        | 40            | 478         |
| 3    | 1         | 1       | -2  | 16   | 168        | 30            | 198         |
| 3    | 7         | 1       | -3  | 16   | 198        | 39            | 237         |
| 3    | 2         | 1       | 1   | 16   | 237        | 28            | 265         |
| 3    | 3         | 1       | 3   | 16   | 265        | 30            | 295         |
| 3    | 4         | 1       | 1   | 16   | 295        | 25            | 320         |
| 3    | 5         | 1       | -1  | 16   | 320        | 31            | 351         |
| 3    | 6         | 5       | -3  | 9    | 351        | 40            | 391         |
| 3    | 8         | 5       | -3  | 8    | 438        | 38            | 476         |

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Table 23. Results of SA and CP Algorithm

| Objective | TWC | Make Span | Utility      | Time (Sec) |
|-----------|-----|-----------|--------------|------------|
| Max(Min) Function | Min | Min | Max |           |
| Goal      | 1484 | 468 | 288 |           |
| CP        | 1514 | 478 | 258.3761 | 300        |
| SA        | 1669 | 493 | 87.30202 | 300        |

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