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Project scheduling based on resource leveling using fuzzy ranking and genetic algorithm: Examination and analysis

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***Abstract*---**Project planning and scheduling is often addressed in the paradigm of combined and fuzzy optimization, which is largely owing to the inherent features of the combination and the ensuing uncertainty in determining the variables, none more significant than the timetables and deadlines of activities. As such, the purpose of the current study is to present a novel metaheuristic model for the aforementioned problem by applying fuzzy ranking and genetic algorithm on the resource leveling indicator. This method will be case-studied on fuzzy numbers needed to express uncertain variables in the real world. Project planning and scheduling using resource leveling and the fuzzy approach is of paramount significance to the industry, as it has shown to greatly ensure the proper and effective use of resources. This research seeks to propose a new model for project scheduling in which the uncertainty of the timetable of the activities and resource levelling are examined at the same time. To generate the initial population in the genetic algorithm, parallel fuzzy prioritization method is used to optimally level the resources, while fuzzy theory is further employed to model the uncertainty of the duration of activities. Moreover, genetic algorithm is used for searching the optimal solution, which is represented by the resource leveling index. The initial population to be included in optimal resource leveling is generated from hybrid 10-tuple prioritization and their fuzzy ranking.

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Introduction

The problem of project planning and scheduling is generally modeled as a hybrid optimization problem that is considered NP-hard* in terms of computational complexity category. NP-hard problems are problems in which the number of variables and constraints are very large and their solution demands massive computational load. As such, heuristics and meta-heuristics are often employed instead of conventional mathematical solutions for solving them. In such problems, runtimes often increase in the form of an exponential function as the number of variables and constraints increase. The current optimization methods employed for solving problems primarily include a large number of variables and constraints that reduce the practical efficiency of problem solving in real-life sample sizes, hence the necessity to employ heuristics and meta-heuristics for solving them. On the other hand, one of the factors that casts doubt on the use of definite methods in solving the project scheduling problem is the uncertain nature of many activities, especially in terms of the duration they require to be completed. Researchers have recently turned to meta-heuristics to solve project scheduling problems with limited resources [52,54,55] and in fuzzy conditions.

Table 1. Different methods of project planning with limited resources

Leu and Hung	Gradual cooling simulation method – not using fuzzy calculations
Zimmerman	Find the minimum time of the whole project (single criterion)
Doeresh	Does not consider resource constraints.
Hapke	single-criterion cooling simulation
Williams	Use of numbers and mathematical logic and probability laws
Yang	Using a prioritized list, not using extra-innovative methods
Easa	linear programming - not considering the estimates of experts
Ahuja	complete counting and definite numbers
Antill and Woodhead	Single-criterion ranking, defuzzied number in project completion time calculations - Use of β distribution function

The current study seeks to propose a novel approach for solving problems of project scheduling using resource leveling under uncertainty. The duration of the activity is specified by a fuzzy number. Moreover, the genetic algorithm technique is employed to examine the optimal and near-optimal resource leveling criteria, which is applied by developing a timetable of non-critical activities in the project and using a critical-chain resource leveling model within an acceptable time frame. In the proposed model, unlike the models presented so far, fuzzy ranking is used instead of selecting random responses as inputs to the resource leveling algorithm.

* Non-deterministic polynomial-time hardness

As such, the problem is solved in two phases. In the first phase, the varying time of project completion and the sequence of the activities are listed, for which the Cheng ranking algorithm is used to prioritize them. The first priorities (for example, the first 3 priorities) of this list will be the input of the resource leveling algorithm, in which the genetic algorithm will be used to find the optimal answer.

Proposing a model for project planning using resource leveling, genetic algorithm and fuzzy ranking

The solution methods considered for the project planning problem in fuzzy conditions are such that first the initial population is obtained from the fuzzy prioritization principle applied to 10 parameters. These parameters are listed in Table 2. The logic behind including the 10 parameters and the necessity of ranking them in projects is their perceivably equal potential to generate a desirable initial solution, and to this end, the current research, the time of completion of the project and the sequence of performing activities is determined using the 10 major and general parameters, after which the feasible solutions are ranked based on Cheng fuzzy ranking algorithm. That is, in this section, the method of performing each activity, fuzzy times of activities, fuzzy times of project completion and fuzzy times of beginning for activities are specified. Hence, the appropriate solutions are inputted into the model and changes in resource allocation are minimized using genetic algorithm according to the constraints. Figure 1 presents the problem and the methodology for solving the model.

Hapke and Slowiniski (2000) conducted the first study on project planning models with limited resources in fuzzy conditions [39]. The case study presented in this article is solved using genetic algorithm and the Cheng's 10 prioritization rules.

Table 2: The 10 popular priority rules employed in this study

1	Fuzzy early start time (EST)
2	Fuzzy early finish time (EFT)
3	Fuzzy late start time (LST)
4	Fuzzy late finish time (LFT)
5	Minimum fuzzy slack (MFSLK)
6	Greatest fuzzy resource demand (GFRD)
7	Shortest fuzzy processing time (SPT)
8	Longest fuzzy processing time (LPT)
9	Most immediate successors (MIS)
10	Least immediate successors (LIS)

Determining alpha-cut representations

Considering the alpha-cut decomposition theorem, each fuzzy set can be attributed to a set of alpha cuts with certain levels α, that represent distinct grades of membership.

$$\alpha_A = \{(x, \mu_A(x) \geq \alpha) \vee x \in X\} \quad \forall \alpha \in [0,1] \tag{5}$$

As such, each fuzzy set can be expressed as follows:

$$A = U\alpha \times \alpha_A \quad \alpha \in [0,1] \tag{6}$$

The defintion of the α-cut implies that the duration of the activity, which is uncertain and represented by fuzzy numbers, determines an upper-bound and lower-bound estimate of the duration of the project under a certain level of α-cut, per the duration defined above. A more definite model of resource leveling can be used to identify optimal solutions for project duration at a given level of α-cut. To this end, the above process is reiterated until all α-cut representations are complete.

Resource leveling

In such problems, it is assumed that resources are unlimited and there is usually a maximum time to complete the project from which the project execution time should not exceed. Despite the great importance and practicality of this type of problems, little research has been performed. Zimmermann [26] divides these problem into the following three categories:

1. Problems in which the maximum amount of resource consumption during the project is minimized.
2. Problems in which resources are provided at the beginning of the project and their level remains constant during the project and the goal is to minimize the total cost.
3. Problems in which the amount of resource consumption or the changes in the level of resources is minimized.

Genetic algorithm

The genetic algorithm was first proposed by Holland, which later proved to be effective in many optimization problems. The genetic algorithm is based on the principle of the survival of the fittest, which seeks to preserve more genetic information from generation to generation. A genetic algorithm involves a plan for reproduction that provides a structural framework for presenting the chromosomes of a generation. Once the successful chromosomes of the generation are selected, a set of genetic operators such as the crossover operator and the mutation operator are used to produce the offsprings of the next generation. Whenever in a generation some chromosomes exhibit higher performances compared to the average population, the genetic information on these chromosomes are more suitable for crossover.

Instead of using a random initial population in this study, rules of parallel prioritization and fuzzy number ranking are used to generate a strong database called the initial population for the purposes of the analysis [39]. The concepts of selection, crossover, mutation, crossover rate and mutation rate are the main foundations of genetic algorithm. The functinality of the genetic operators on the solutions depends on the problem under study. Attempts are directed at defining genetic operators in such a way that the offsprings perform better than the parents [57-59]. Another point to consider in defining genetic operators is to maintain the feasibilty and integrity of the solution. This should also be the case while selecting the initial solutions, hence the ineffeciency of completely random answers. Therefore, one of the basic steps of the genetic algorithm is to determine a method for generating sound initial solutions [39].

Overall, the steps of implementing a genetic algorithm for solving a problem is as following:

1. Offering a general solution to the problem which is also suitable for the genetic algorithm.
2. Determining the method of production of the initial population, which includes potentially feasible solutions.
3. Determining the criteria for moving towards a a better solution by optimizing in the objective function.
4. Identifying genetic operators such as crossover, mutation, and inversion that affect offspring during reproduction.
5. Determining the parameters of genetic algorithm such as population size, number of offspring, crossover rate and mutation rate [11].

In a genetic algorithm, the set of potential solutions to a problem are represented as a population of chromosomes, each chromosome representing a possible solution. Chromosomes evolve through generations. Offsprings are produced by merging two parent chromosomes and the chromosome interference (or modification) operator using the mutation operator. During each generation, chromosomes are evaluated according to matching functions. Matching chromosomes have more chance of survival. The final chromosomes will be the optimal or near-optimal solutions to a problem. The genetic algorithm-based approach has the same disadvantage as the original models (e.g., neither model gauarntees the optimal solution). However, near-optimal solutions of the genetic algorithm can provide the required information for informed managerial decisions [39].

The following features have led to the widespread application of genetic algorithms in project planning:

1. Genetic algorithm works with coded parameters, not with the parameters themselves
2. The genetic algorithm starts the search process with a set of points, not a single point.
3. The genetic algorithm uses probabilistic, rather than definite, rules to move from one stage to another.
4. Modeling project planning problems with resource constraints in the form of genetic algorithm is readily possible.

5. Suitable efficiency of this method for project planning problems with limited resources in terms of solution time and quality of solutions [52-54].

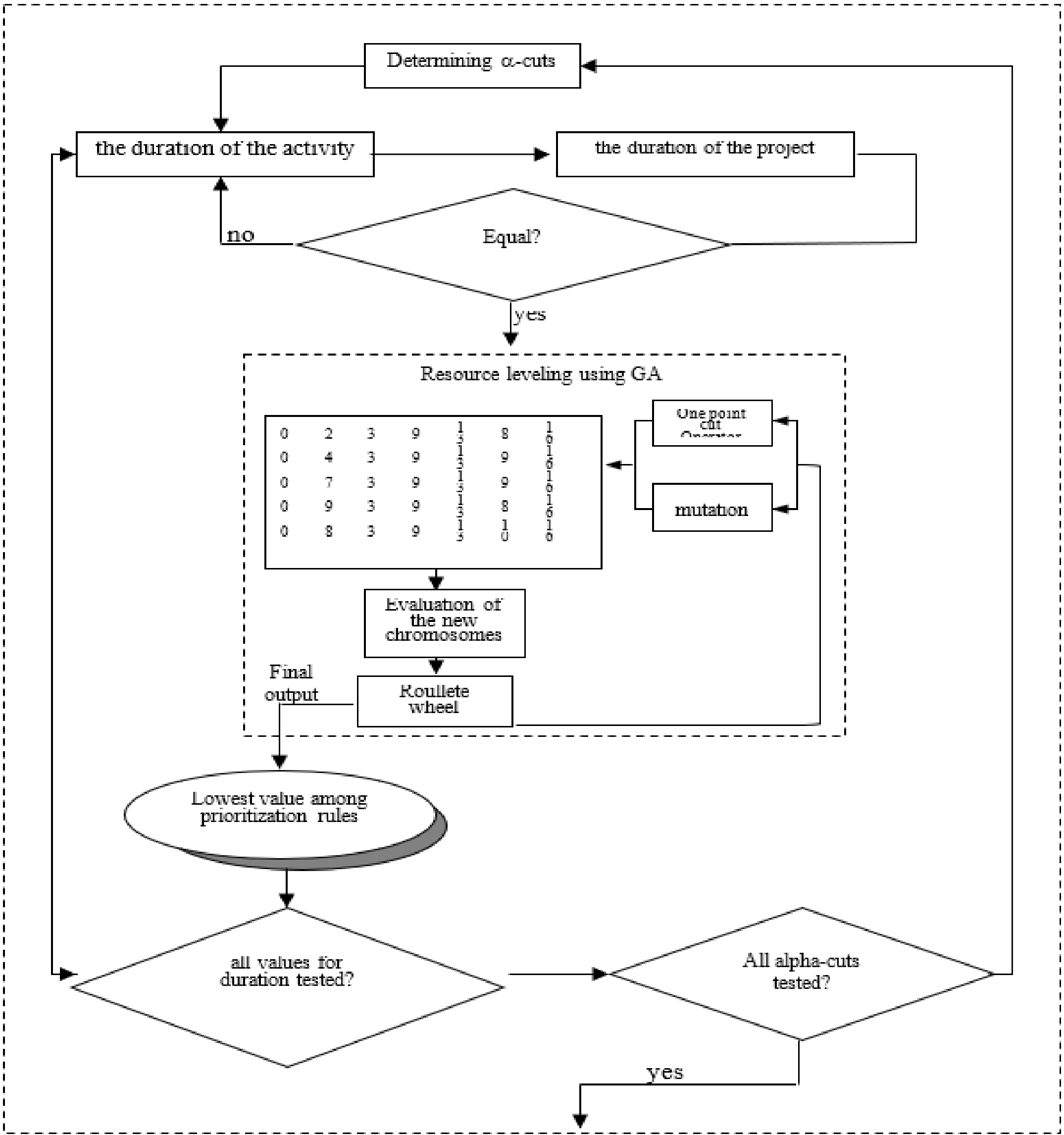

Figure 1: The flowchart of the proposed model

Leveling resources using a fuzzy approach

Previous research has indicated that the main purpose of resource leveling is to set specific days for all activities so that the common resource histogram reaches a convex quadrilateral for uniformly leveling resources. It is trivial that that the feasible space must be convex [51-50]. In resource leveling operations, the problem of resource leveling can be stated as follows:

Minimize $\tilde{L}$
Subject to

$$\tilde{L} = \frac{\sum_{q=1}^{T} \left\{ \sum_{i=1}^{n} \left| r_i \times x_{\mathrm{iq}} - \frac{\sum_{q=1}^{T} \mathrm{Rq}}{T} \right| \right\}}{T}$$

$$\mathrm{Rq} = \sum_{i=1}^{n} r_i \times x_{\mathrm{iq}} \forall q$$

$\mathrm{Rq} \le b \forall q$ $\quad \tilde{T}_i - \tilde{ES}_i \le T\tilde{F}_i \forall i$ $\quad q \times x_{\mathrm{iq}} \le \tilde{t}_i + \tilde{d}_i \forall i, q$ $\quad \tilde{t}_i x_{\mathrm{iq}} \le q \forall i, q$ $\quad x_{\mathrm{iq}} \in \{0,1\}$ $\quad t_1 = 0, \tilde{t}_i \ge 0 \forall i \ne 1$

In which x_{iq} is a dummy variable equal to one if the activity i is performed in day q. r_i is the resources required for activity i. b is the total of available resources. $\tilde{ES}_i$ is the early start of activity i.. TF_i is the total floating time of activity i. d_i is the duration of activity. T_i is fuzzy time of the start of the activity. T is the time of completion of the project, and R_q is the resources required for day q. L is the parameter that indicates the mean of the absolute difference between the volume of resources used, and Constraint (3) indicates the amount of resource needed for each day. The resources used in this section should not exceed the resource constraints [4].

Constraint 5 states that the start times of activities in this section should be such that the same fuzzy time of project completion is achieved in the ranking phase. That is, the start time of activities that a solution to resource leveling problem offers must be derived from changes in the fuzzy early start time of activities in the floating time. Constraint 6 and 7 check whether activity i is performed on day q or not?Resource leveling is generally achieved by the relocation of non-critical activities within existing floating buffer (usually total floating time).

Fuzzy resource leveling using genetic algorithm [56]

When using a genetic algorithm, chromosomal patterns and the functionality of crossover and mutation operators will depend on the problem. Using the project time network, the coding of chromosomes and genetic algorithm operators used in this paper can be outlined as follows: When using genetic algorithms for resource leveling problems, each character in the chromosome string is considered the appropriate date to start the activity. In this paper, a single point cut operator and a uniform mutation operator are used for achieving near-optimal solutions. In this method, single point cuts in parent arrays are randomly selected and the right parts of the two arrays are exchanged to create child arrays.

Assume that the two chromosomes belong to the parents $X = \{x_1, \ldots, x_n\}$ and $y = [y_1, \ldots, y_n]$.
If the arrays are mixed after position k, the resulting children would be as follows:

$$x' = [x_1, x_2, x_3, \ldots x_k, y_{k+1}, y_{k+2}, \ldots, y_n]$$
$$y' = [y_1, y_2, y_3, \ldots y_k, x_{k+1}, x_{k+2}, \ldots, x_n]$$

By combining the notion of resource leveling, the concept of cut α-cuts and genetic algorithm, the operation of the optimal fuzzy model of project planning can outlined as follows.

This model includes 4 subsystems:

1. Generating the duration of the activity
2. Determining the duration of the project implementation, which has already been determined as a maximum
3. Resource leveling
4. Output

Each subsystem has its own purpose. Subsystem 1 is created to determine the duration of activities that occur at a certain level of α. Then, subsystem 2 determines the lower-bound and upper-bound limits of the project duration are determined at a certain level of α, which is based on the duration of the activity and the sequential priority of the activities. Subsystem 3 corresponds to resource leveling, which is selected based on the duration of the project. From the comparison of the results obtained from subsystems 1 and 2, if the calculated duration for the execution of the project is not equal to the selected duration, the combination is excluded from the model. But if they are equal, each of the desirable combinations are inputted into subsystem 3 to determine the minimum value of the index. Subsystem 3 generates a set of chromosomes to indicate activity start times. Each character on a chromosome represents the start date of the activity, the amount of which is limited within the lower-bound and upper-bound limits. The single-point cut operator and the uniform mutation operator are used to generate offspring chromosomes.

The concepts of uniform mutation and single-point cut operators are shown in Figure 2 [51]. The values of the source leveling index (matching values in the genetic algorithm) are used to select resistant chromosomes for the next generation, and according to the objective function in Equation 2, the remaining chromosomes for the next generation are selected according to the roulette wheel principle. That is, the probability of selection for the k chromosome is proportional to the ratio $f_k/\sum_{j=1}^{pop-f_j}$, where f_k is the amount of chromosome matching. The above process is reiterated for all the desired combinations for the duration of the activity (for example, the calculated project length is equal to the selected length for the project). In the final stage of the resource leveling subsystem, the minimum value for all leveling indicators is considered as the optimal and near-optimal solution for the selected project duration at a given α-cut. This value as well as the duration of activity and the amount of α cut are transferred to the output subsystem. This process is repeated from subsystem 1 to subsystem 3 to test all possible values for the duration of the project within the framework of possible ranges as well as all α-cut presentations (e.g., from 0 to 1). In the final output subsystem, all values related to the resource leveling index and the corresponding duration and α-cut values are collected for data analysis and graphing [39].

Determining the initial population of genetic algorithm using Brooks algorithm

In standard genetic algorithms, the initial population is obtained randomly. Nevertheless, randomly generated initial populations have shown to be unreliable for prioritizing activities in resource leveling, as there would no guarantee as to their efficacy. As such, the fuzzy parallel scheduling method has proven to offer some valid solution in the initial answer population, especially in fuzzy conditions and while working with limited resources. That is, the activities are first ranked according to a specified prioritization rule and according to the initial solutions determined in the previous step for the duration of the activities in fuzzy conditions and then scheduled according to the limited resources available using the parallel method.

The reason for using the parallel scheduling method is that it has shown to outperform its serial counterpart in solving resource allocation problems. In the parallel method, all activities that are ready for planning are considered at any given time. In this method, the activities are sorted according to a scheduling rule in Table 1 and then scheduled according to the availability of resources. If an activity is not programmable at a particular time due to the unavailability of the resources required, the next activity with the highest priority is selected from the list of programmable activities that have been arranged for scheduling at that time. The algorithm of the parallel scheduling method is given below. The planning of the activities in this research is based on the fuzzy heuristics model because it is able to make the best use of time, resources and tools.

Prioritizing the solutions to input into the genetic algorithm

The criterion of better fit of the initial solutions to be used as input to the genetic algorithm of resource leveling is determined using the final sequential ranking. That is, after determining the sequence of the activities, the fuzzy time of activities, and the fuzzy time of project completion can be calculated, which can be prioritized using the fuzzy ranking algorithm. The first three priorities are inputted into the genetic algorithm with the resource leveling index. In the problem of resource leveling, $\tilde{t}$ is used to select the best solution. Defuzzied $\tilde{t}$ is the fuzzy number of the resource leveling index.

Genetic operators

The choice of operators is the most important part of the genetic algorithm. The genetic algorithm performs its searches on the solution space using the genetic operators. The manners by which operators are defined depends on the solution to the problem. Operators must also be defined in such a way that the generated solutions are vindicated.

Selection operator

After determining the population of the solution, the value of the objective function or the goodness of fit for each of the solutions is calculated. The solutions are sorted from best to worst in terms of the value of their objective function. Owing to their crossover rate, the more optimal solutions are kept for the crossover operation while others are excluded. Thus, the number of population solutions decrease from N_{pop} to N_{keep}.

The roulette wheel weighting (cost weighting) method is used to select two solutions for the crossover operation from the remaining solutions. In this method, for each of the remaining solutions, the probability of being selected as a parent is calculated. The probability that the nth solutions will be chosen as one of the parents is calculated from the following equation:

$$P_n = \frac{C_n}{\sum_{i=1}^{N_{keep}} C_i} \tag{11}$$

Where C_i is the value of the objective function for the i-th solution. Thus, for the problem of leveling resources, the probability of choosing the nth solution as a parent is calculated using the following equation:

$$P_n^r = \frac{t_n}{\sum_{i=1}^{N_{keep}} (t_i)} \tag{12}$$

After calculating the selection probability for each of the solutions and calculating the cumulative probability, random numbers can be generated to determine the candidate solution for parents. N_{pop} - N_{keep} parent pairs must be selected for the next generation population to hit N_{pop} again.

Crossover operator

The crossover operator is suitable for the fuzzy time chromosomes of the activity and the fuzzy time of the beginning of the activity is the single point cut operator. For a single-point cut operator, as shown in Figure 2, a cut point is randomly selected on the parent chromosomes, and the two arrays to the right of the two parents are exchanged to create the offspring chromosomes. For fuzzy time chromosomes with trinagular numbers, the cut points must be a multiple of 4, while it must a multiple 4 for trapezoidal numbers [39-46].

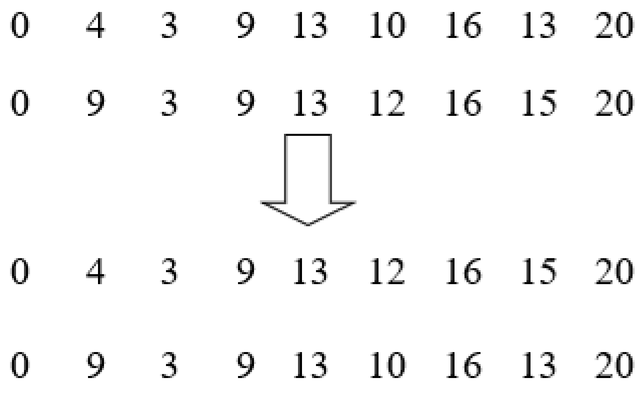

Figure 2: Genetic operators for 2 parents and 2

For chromosomes of fuzzy duration of activities and fuzzy time of beginning of activities, a uniform mutation operator is used. The uniform mutation operator randomly selects a gene and replaces the number belonging to that gene with another random number from a given interval. For fuzzy duration chromosomes of activity, the interval at which the mutation operator acts on the genes is the set of times at which an activity can be performed according to different methods.

For the problem of fuzzy resource leveling, where the genes represent the time at which fuzzy activities begin, the interval at which the mutation operator acts on the genes will be the floating time of the activities. For example, consider a project with five activities whose fuzzy start times are like the following chromosome:

0	0	0	6	25	30	2	5	10	16	25	30	45	45	53

The new chromosome can be as follows by performing a uniform mutation on the fuzzy time of the second activity with the fuzzy slack time (2.5.7), with the random fuzzy slack time (1.3.5) added to the start time of activity 2.

0	0	0	7	28	35	2	5	10	16	25	30	45	45	54

The role of the roulette cycle is to calculate the probability of assigning each chromosome in each generation [39]. How it works is as follows:

1. Selecting chromosomes to cut the next generation
2. Formation of the next generation population by selecting n1 solutions from the rest of the previous generation and n2 new solutions resulting from cutting
3. Mutation based on mutation rate on new generation chromosomes.

The purpose of the roulette wheel is to calculate the probability of assigning each chromosome in each generation [39], which functions as follows:

1. Selecting chromosomes to cut the next generation
2. Formation of the next generation population by selecting n1 solutions from the rest of the previous generation and n2 new solutions resulting from cutting
3. Performing mutation based on mutation rate on new generation chromosomes.

Convergence

In genetic algorithms, as generations are produced, the population is filled with chromosomes that outperform the previous ones. Thus, the average measure of goodness of fit moves towards the overall optimal. An ideal algorithm should be able to maintain a high degree of variability during transmission from generation to generation. Otherwise, the population may converge before the desired solution is obtained. To prevent convergence, the current study employed the following features in the model:

1. Considering that the initial population is formed based on 10 varying prioritization rules, the variety of possible answers is high, which reduces the probability of convergence.

2. The fuzzy nature of the problem under study, as well as the matching of the chromosome structure of the problem increase the variability of the solutions, as a result of which the probability of convergence decreases.
3. Applying a mutation operator at a higher rate each time the loop is repeated can minimize the convergence of the solutions.

Algorithm for generating initial solutions using fuzzy rules of parallel prioritization and fuzzy ranking [53]

1. First, the fuzzy time required to perform the activities by different alpha-cuts and the required resources for each activity are specified.
2. Next, the rules of parallel prioritization using the 10 prioritization rules are applied on the data ouputted fron the previous step and based on the resulting sequence, the time required to complete the project for each case is obtained as a fuzzy number.
3. According to the fuzzy ranking algorithm, these fuzzy numbers are prioritized and inputted into the model as the initial population for optimal resource leveling (In this step, the fuzzy time of start and end of activities and floating times can be calculated for each of the inputs).

Fuzzy number ranking

The ranking of fuzzy number is an important issue in project planning and scheduling. Although a plethora of ranking methods have been proposed thus far, there is no single method that can achieve a desired result for any given scenario. Some of these methods may produce accurate results while some others may not.
The Chang distance is used to compare fuzzy numbers, which is based on the calculation of the central region $(\bar{x}|0,\bar{y}_0)$ to obtain the distance index. $(\bar{x}|0,\bar{y}_0)$ determines the central values in the horizontal and vertical axes. The algorithm for finding a triangular and trapezoidal fuzzy number is as follows:

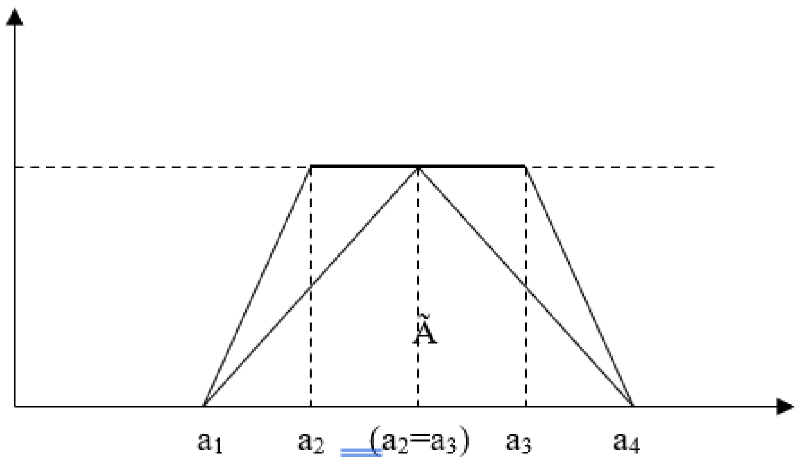

Figure 4. Trapezoidal and triangular fuzzy numbers [39].

$$\mu_{\tilde{A}} = \begin{cases} \mu_{\tilde{A}}^{L}(x) = \frac{x-a_1}{a_2-a_1} ؛ a_1 \le x \le a_2 \\ 1 ؛ a_2 \le x \le a_3 \\ \mu_{\tilde{A}}^{R}(x) = \frac{a_4-x}{a_4-a_3} ؛ a_3 \le x \le a_4 \\ \circ ؛ \end{cases} \quad (13)$$

$\mu_{\tilde{A}}^{L}: [a_1, a_2] \to [0,1]$ is strictly uniform on the left, and its corresponding inverse function is represented by $g_{\tilde{A}}^{L}(x)$, and similarly, $\mu_{\tilde{A}}^{R}(x): [a_3, a_4] \to [0,1]$ is continuous and uniform on the right, and its inverse function is represented by $g_{\tilde{A}}^{R}(x)$. These functions can be integrated because of the continuity condition, so the center point ($x_\circ$, $y_\circ$) of the fuzzy number $\tilde{A}$ is as follows:

$$\tilde{x}_\circ(\tilde{A}) = \frac{\int_{a_1}^{a_2}[x\mu_{\tilde{A}}^{L}(x)]dx + \int_{a_2}^{a_3} x dx + \int_{a_3}^{a_4}[x\mu_{\tilde{A}}^{R}(x)]dx}{\int_{a_1}^{a_2}[\mu_{\tilde{A}}^{L}(x)]dx + \int_{a_2}^{a_3} dx + \int_{a_3}^{a_4}\mu_{\tilde{A}}^{R}(x)dx}$$

$$\tilde{y}_\circ(\tilde{A}) = \frac{\int_0^1[yg_{\tilde{A}}^{L}(y)]dy + \int_0^1[yg_{\tilde{A}}^{R}(y)]dy}{\int_0^1 g_{\tilde{A}}^{L}(y)dy + \int_0^1 g_{\tilde{A}}^{R}(y)dy} \quad (14)$$

The ranking index can be presented as follows:

$R(\tilde{A}) = \sqrt{\quad}$

For trapezoidal fuzzy numbers, Eq. (14) can be simplified as follows:

$$\bar{x}_\circ = \frac{a_4^2 + a_3^2 - a_1^2 - a_2^2 + a_3 \times a_4 - a_1 \times a_2}{3(a_3 + a_4 + a_1 + a_2)}$$

$$\bar{y}_\circ = \frac{a_1 + 2\times a_2 + 2\times a_3 + a_4}{3(a_1 + a_2 + a_3 + a_4)} \quad (15)$$

Since $\tilde{A}_i$ and $\tilde{A}_j$ are fuzzy numbers in the set R, ranking indicators corresponding to fuzzy numbers are performed using the following properties:

$$R(\tilde{A}_i) \rangle R(\tilde{A}_j) \Rightarrow \tilde{A}_i \rangle \tilde{A}_j \qquad R(\tilde{A}_i) = R(\tilde{A}_j) \Rightarrow \tilde{A}_i = \tilde{A}_j \qquad R(\tilde{A}_i) \langle R(\tilde{A}_j) \Rightarrow \tilde{A}_i \langle \tilde{A}_j \quad (16)$$

In this paper, the initial population to enter the genetic algorithm, and the fuzzy numbers that indicate the completion time of the project in different sequences of activities are determined using Eqs. (16).

The problem-solving algorithm using genetic algorithm on resource leveling prioritization criteria

1. Select the appropriate solution for the initial population.
2. Determine the general float times for the activities.
2. Determine the □-cut presentation.

3. Comparing the duration of the project and the duration of the activity
4. If the factors in step 4 are equal, go to step 6.
5. Given the float times of the fuzzy time chromosomes, form the beginning of activities for the initial population responses.
6. Calculate the value of the objective function for each of the solutions to determine the optimal of the population (evaluation).
7. Having in mind the crossover rate, keep the solutions with good fit for performing the crossover operation and exclude the other solutions.
8. Use the roulette wheel method to select the chromosomes for reproduction, and perform the crossover operation using the single-point cutting method for fuzzy time chromosomes of the start of the activities.
9. Perform the mutation operation on the new population using the uniform fuzzy mutation operator and the proposed mutation rate.
10. Reiterate steps 3 to 10 until the stop condition, i.e., the number of generations, is reached.
11. Determine the minimum value for all resource leveling prioritization rules.
12. Have all possible values for the duration of the project been tested within the feasible range? If is yes, go to step 14, otherwise go to step 4. (In this paper, the different values considered for α range from 0.1-0.9).
13. Have all cutting surfaces been tested? If yes, go to step 15.
14. 15- Print the minimum level of the leveling index, the relevant duration and the amount of α-cut.

Case study

The assembly procedure in the Food&Drug industry is perceived to be consisted of 14 activities. The priority of the relationships between activities is presented by the network structure of Figure 1. In planning this project, three different types of renewable resources are deemed essential throughout the project, the amounts of which are limited. The availability of resources 1, 2 and 3 in each round is shown in Table 1. Due to the nature of uncertainty in some activities, the times required to perform the activities are considered fuzzy triangular. Project information is listed in Table 1, in which R_n represents the nth renewable source. The results of fuzzy prioritization calculations are presented in Tables 2 and 3 using 10 priority rules.

The purpose of scheduling is to minimize assembly time. That is, the goal is to determine the start times of activities in such a way that the project completion time and the utilized resources are optimized per the requisites of resource leveling. The results from implementing the parallel prioritization algorithm and ranking the resulting fuzzy numbers indicated that sequences based on EST, LFT and SPT indices would generate better results. As such, the project completion times based on the aforementioned index are inputted into the resource leveling model as the initial population.

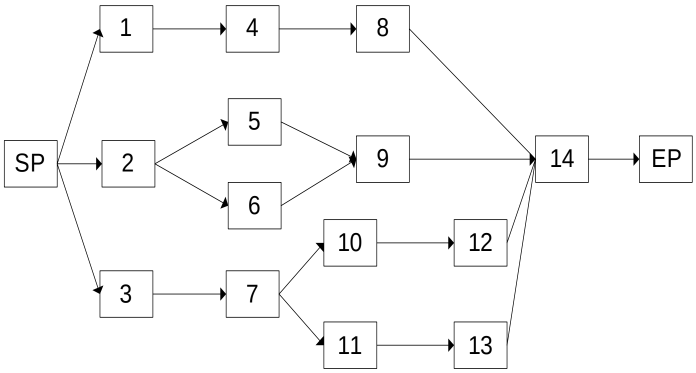

Figure 1: Project network diagram

Table 1: Required time and resources

Activity no.	Duration	R_1	R_2	R_3
1	(15.19.25)	1	3	4
2	(10.13.20)	1	3	2
3	(8.10.15)	0	0	4
4	(20.23.36)	0	3	5
5	(10.15.20)	0	2	4
6	(6.9.15)	0	1	2
7	(5.9.15)	1	2	2
8	(18.24.30)	1	3	4
9	(10.13.25)	1	2	3
10	(5.8.12)	1	2	2
11	(8.11.15)	1	2	2
12	(5.5.5)	1	0	2
13	(4.6.9)	0	2	2
14	(10.10.10)	2	5	5

The □-cut presentation was used here to determine the fuzzy time of execution of activities.

Each of the numbers in the second column of the table above is the duration of the activities, which is estimated as a triangular fuzzy number. The numbers for the third to fifth columns represent the volume of resources needed to perform each activity.

Generation of the initial population as input to the genetic algorithm model

To generate the initial population for the genetic algorithm model, different sequences of activities should be generated and hence ranked by calculating the time of completion of the project for each (according to the 10 rules) using Cheng algorithm.

Table 2: Application of parallel prioritization rules (part 1)

Activity no.	ES \{$\tilde{T}_i$	EF \{$\tilde{T}_i$	LS \{$\tilde{T}_i$
1	(0.0.0)	(15.19.25)	(0.0.0)
2	(0.0.0)	(10.13.20)	(0.18.53)
3	(0.0.0)	(8.10.15)	(0.34.66)
4	(15.19.25)	(35.46.60)	(15.19.25)
5	(10.13.20)	(20.26.40)	(3.32.63)
6	(10.13.20)	(16.23.35)	(8.38.68)
7	(8.10.15)	(13.19.30)	(14.44.74)
8	(35.46.60)	(53.70.91)	(32.36.61)
9	(20.26.40)	(30.45.65)	(28.55.81)
10	(13.19.30)	(18.27.42)	(36.57.81)
11	(13.19.30)	(21.30.45)	(29.53.79)
12	(18.27.42)	(23.32.47)	(48.65.86)
13	(21.30.45)	(25.36.54)	(44.64.87)
14	(53.70.91)	(63.80.101)	(53.70.91)

Table 3: Application of parallel prioritization rules (part 2)

Activity no.	LF \{$\tilde{T}_i$	MFSLK = LS \{$\tilde{T}_i$ − ES \{$\tilde{T}_i$	GFRD = $\tilde{d}_i \sum_{i\in R} k_{\mathrm{ir}}$
1	(15.20.25)	(0.0.0)	(120.152.200)
2	(3.32.63)	(0.18.53)	(60.78.120)
3	(14.44.74)	(0.34.66)	(32.40.60)
4	(35.46.61)	(0.0.0)	(160.184.288)
5	(23.46.73)	(0.18.53)	(60.90.120)
6	(23.46.73)	(0.24.57)	(18.27.45)
7	(29.53.79)	(0.34.66)	(25.45.75)
8	(53.70.91)	(0.0.0)	(144.192.240)
9	(53.70.91)	(0.26.61)	(60.78.150)
10	(48.65.86)	(6.38.68)	(25.40.60)
11	(44.64.87)	(0.34.66)	(40.55.75)
12	(53.70.91)	(6.38.68)	(15,15,15)
13	(53.70.91)	(0.34.66)	(16.24.36)
14	(63.80.101)	(0.0.0)	(120.120.120)

Table 4: duration and project completion time for the 10 prioritization rules

Heuristic rules	Sequence of activities	Completion time
ES \{$\tilde{T}$	1.2.3.7.5.6.4.10 11.12.9.13.8.14	(67.88.105)
EF \{$\tilde{T}$	3.2.1.7.6.10.5.11 12.13.9.4.8.14	(75.98.144)
LS \{$\tilde{T}$	1.4.2.5.3.6.7.8	(75.99.132)

	11.9.10.13.12.14	
LF \{T	1.2.3.4.6.5.7.11 10.8.9.13.12.14	(60.86.121)
MFSLK	1.4.8.2.5.6.9.3 7.11.13.10.12.14	(99.130.177)
GFRD	1.4.8.2.5.6.9.3 7.11.10.13.12.14	(93.124.169)
SP \{T	3.2.1.7.6.5.4.10 11.9.8.12.13.14	(63.82.110)
LP \{T	1.4.8.2.5.6.3.9.7 11.10.13.12.14	(89.120.150)
MIS	1.3.4.8.2.5.6.9.7 11.10.13.12.14	(86.130.150)
LIS	2.3.1.7.4.5.6.10 11.9.8.12.13.14	(68.88.115)

After ranking the completion times, the three best solutions are inputted to the model as the initial population for the purposes of resource leveling.

Table 5: Start and end times of activities and floating time according to the order of activities and the initial population (EST) - Solution 1

Activity no.	LS \{T_i	ES \{T_i	LS \{T_i − ES \{T_i
1	(0.0.0)	(0.0.0)	(0.0.0)
2	(0.18.53)	(0.0.0)	(0.18.53)
3	(0.34.66)	(0.0.0)	(0.34.66)
4	(15.19.25)	(15.19.25)	(0.0.0)
5	(3.32.63)	(10.13.20)	(0.19.43)
6	(8.38.68)	(10.13.20)	(0.25.48)
7	(14.44.74)	(8.10.15)	(6.34.59)
8	(32.36.61)	(32.46.61)	(0.0.0)
9	(28.55.81)	(20.26.40)	(8.29.41)
10	(36.57.81)	(13.19.30)	(23.38.51)
11	(29.53.79)	(13.19.30)	(16.34.49)
12	(48.65.86)	(18.27.42)	(30.38.44)
13	(44.64.87)	(21.30.45)	(23.34.42)
14	(53.70.91)	(53.70.91)	(0.0.0)

Table 6: Start and end times of activities and floating time according to the order of activities and the initial population (EFT) - Solution 2

Activity no.	LS \{T_i	ES \{T_i	LS \{T_i − ES \{T_i
1	(0.0.0)	(0.0.0)	(0.0.0)
2	(0.17.50)	(0.0.0)	(0.17.50)
3	(8.35.69)	(8.10.12)	(0.25.57)
4	(10.14.20)	(10.14.20)	(0.0.0)

5	(15.20.26)	(12.15.20)	(3.5.6)
6	(17.27.35)	(12.15.20)	(5.12.15)
7	(16.38.50)	(16.33.45)	(0.5.5)
8	(29.46.61)	(29.46.61)	(0.0.0)
9	(28.45.59)	(20.37.50)	(8.8.9)
10	(12.26.52)	(10.20.42)	(2.6.10)
11	(30.55.69)	(14.25.29)	(16.30.40)
12	(24.38.51)	(20.29.40)	(4.9.11)
13	(25.43.56)	(21.38.50)	(4.5.6)
14	(59.67.85)	(59.67.85)	(0.0.0)

Table 7: Start and end times of activities and floating time according to the order of activities and the initial population (SPT) - Solution 3

Activity no.	LS \{$\tilde{T}_i$	ES \{$\tilde{T}_i$	LS \{$\tilde{T}_i$ − ES \{$\tilde{T}_i$
1	(4.8.11)	(0.3.3)	(4.5.8)
2	(2.9.15)	(2.9.15)	(0.0.0)
3	(4.23.41)	(9.16.29)	(5.7.12)
4	(16.22.35)	(12.16.25)	(4.6.10)
5	(20.26.35)	(20.26.35)	(0.0.0)
6	(27.34.47)	(15.20.30)	(12.14.17)
7	(20.35.50)	(21.32.43)	(1.3.7)
8	(36.53.68)	(30.35.42)	(6.18.26)
9	(40.52.63)	(40.52.63)	(0.0.0)
10	(22.37.59)	(17.27.34)	(5.10.16)
11	(21.35.44)	(17.27.34)	(4.8.10)
12	(29.41.49)	(25.34.40)	(4.7.9)
13	(37.46.59)	(33.40.48)	(4.6.11)
14	(63.70.86)	(63.70.86)	(0.0.0)

Then each of the appropriate solutions is inputted to the model by considering the intercept rate and mutation rate of 0.8 and 0.6 and stop condition n = 100, the results on which are as follows:

Solution 1: $\tilde{t}$ =(0.50, 0.60, 0.65)
Solution 2: $\tilde{t}$ =(0.50, 0.55, 0.60)
Solution 3: $\tilde{t}$ =(0.65, 0.70, 0.80)

The fuzzy number ranking method indicates that the second solution provides the best timing for the project according to the criteria of the resource leveling index.

Figure 2 shows the process of improvement in the solutions.

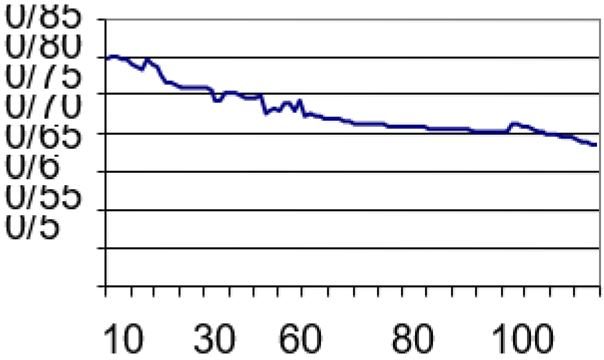

Figure 2: Resource leveling for the proposed algorithm

The findings from Figure 2 indicate the higher the number of generations in the genetic algorithm, the lower the resource leveling index. That is, as the resource leveling index decreased, variations in resource allocation are minimized.

Accuracy and Precision

12 sample problems with varying number of activities as specified in Table 8 are employed to examine the proposed model in this paper. The results of the proposed method were compared with those of Lingo in terms of solution time. Activity time is a triangular fuzzy number that is represented as (a, b, c). Fuzzy calculations are performed on the duration of activities to calculate the end time of the project. The resulting fuzzy numbers, which represent the project completion time, are fuzzy ranked and the first three priorities enter phase 2. In Phase 2, the solutions are reprioritized based on the resource leveling index and using the genetic algorithm, following which the near-optimal solution(s) are obtained.

Table 8. Results of solving sample problems using the proposed algorithm and Lingo

Problem no.	Number of activities	Number of methods	Genetic algorithm solution time (seconds)	Lingo solution time (seconds)
1	20	2	30	28
2	20	3	32	30
3	20	4	43	39
4	20	5	50	44
5	20	6	57	52
6	20	7	63	56
7	40	2	720	1280
8	40	3	790	2040
9	40	4	9859	2090
10	40	5	980	3060
11	40	6	1660	3640
12	40	7	1960	4860

It is evident from Table 8 that the proposed method is more efficient than mathematical programming methods. The examination of the sample dataset revealed the following results:

1. The genetic algorithm performs much better compared to Lingo, although Lingo generates slightly better results in smaller samples.
2. The efficiency of genetic algorithms increases with the complexity of problems and their size.
3. Increasing the number of execution methods increases the complexity of the problems with greater effects compared to increasing the number of activities.
4. The longer the project completion time, the resource leveling method can perform better at resource allocation.

Conclusion

It is a well-established fact that fluctuations in the level of resource consumption increase the costs of releasing and reusing resources during project implementation. To solve this problem, this study presented a comprehensive method for leveling resources using genetic algorithm and fuzzy ranking. The performance of the proposed model was evaluated using 12 data sets from the subject literature, the results from which were compared with other methods. The results suggested that the proposed method outperforms similar models especially in complex and large problems. In addition, the proposed model is more in line with the real-life scenarios, as it levels all the resources simultaneously and offers realistic time-tables highly consistent with the opinions of the project experts. Therefore, the proposed model can be provided to managers and planners as an efficient tool for leveling resources and plotting more realistic project planning schemes. The proposed model was shown to exhibit the following features:

1. Using fuzzy set theory, the model is able to efficiently determine the time required to perform activities.
2. The meta-heuristic method of genetic algorithm results in several solutions with near-optimal solutions.
3. Using fuzzy ranking, the initial possible solutions are not considered randomly, leading to reduced computational complexity and runtime of the algorithm.
4. Since the ranking rules are not deemed superior to one another, all the 10 prioritization rules affecting the completion time of the project are examined and, in each project, the most important parameters are identified according to constraints.
5. The best solution is determined using the resource leveling index along with the application of resource constraints.
6. Comparing the results of 12 problems solved by Lingo software and the proposed method shows the superiority of the proposed method (in terms of execution time), especially in large and NP-hard problems.
7. The longer the project is completed, the smoother the level of resource allocation will be.

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