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The use of Fuzzy Clustering Chaotic-based Differential Evolution to the Resource Leveling of Construction Projects

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Abstract

The Critical Path Method is one example of a network scheduling approach that is extensively used in the construction industry to establish project schedules. However, these timetables often lead to considerable resource variations, which make it impossible and expensive for contractors to carry out their work according to the schedule. Therefore, construction managers are needed to carry out resource-leveling operations in order to ensure that the resource profile is consistent. This study presents a unique optimization model that has been given the term Fuzzy Clustering Chaotic-based Differential Evolution for addressing Resource Leveling (FCDE-RL). In order to solve difficult optimization issues, we devised a method called Fuzzy Clustering Chaotic-based Differential Evolution, or FCDE for short. This method combines the traditional differential evolution algorithm with fuzzy c-means clustering and chaotic approaches. The chaotic environment was purposely created and maintained in order to avoid the new strategy from prematurely converging. In the meanwhile, fuzzy c-means clustering operates as numerous multi-parent crossover operators to make effective use of the information provided by the population in order to improve convergence. Experimentation and investigations have shown that the newly developed optimization model is a potential option that may help project managers cope with the issue of resource leveling in building projects.

Key words: Construction Management; Resource Balancing; Fuzzy Clustering; Chaotic; Differential Evolution;.

1. Introduction

In the current economic climate, the capacity of a construction firm to successfully manage its resources is one of the most important factors determining whether or not it will continue in business [1]. Inappropriate management of resources might potentially drive up operating costs and perhaps give birth to financial and schedule issues. It is possible that the length of the project will need to be extended due to the excessive resource demands at the construction site. Due to the fact that the contractor will not be able to complete the project by the date that was previously set, the owner is at risk of incurring financial loss since the facility will not be available [2]. In addition, delays in construction often result in arguments between the many parties involved, greater overhead expenses, a deterioration of reputation, and, on occasion, the collapse of the project [3, 4]. As a result, the management of available resources is an essential activity that must be carried out in an exhaustive manner throughout the planning phase.

The resources used in the construction industry may be broken down into five categories: labor, equipment, materials, financial resources, and expertise. Proper management of these resources is essential to the successful completion of any project [2]. However, building schedules that are created using network scheduling algorithms often result in unfavorable variations of the resources, making it difficult, inefficient, and expensive for contractors to put such plans into action [5]. As a result, construction managers are obligated to carry out the process of schedule adjustment in order to minimize variations in resource use that are not essential to the successful completion of the project.

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The changes in resource availability are, needless to say, a bothersome problem for the contractor [6]. The reason for this is because it is costly to employ people on a short-term basis and it is also expensive to lay off personnel in response to variations in the resource profile. In addition, if the resources are unable to be handled effectively, it is possible that they may surpass the supply capabilities of the contractor, which would result in a timetable delay. In conclusion, the contractor is responsible for keeping a certain amount of resources available even when demand is low. These factors unquestionably have a negative impact on the profits of building enterprises.

The process of balancing out the availability of resources is referred to as resource leveling and has been the subject of in-depth investigation by a large number of scholars [5, 7, 8]. When it comes to resource leveling, the goal is to reduce oscillations in the pattern of resource utilization as well as peaks in demand as much as possible [9]. This method attempts to stabilize the length of the project while reducing the amount of variance in the resource profile. This is accomplished by moving non-essential operations within their available floats. The problem of resource leveling in a building project may be tackled using a wide number of ways, ranging from mathematical methods to heuristic approaches and even evolutionary methods (e.g. Genetic Algorithm, Particle Swarm Optimization, Differential Evolution, etc.).

Differential Evolution (DE) [10, 11] has, as of late, been generating an increasing amount of attention among academics, who have been investigating the capabilities of this algorithm in a broad variety of different applications. DE is a population-based stochastic search engine that has shown to be both successful and efficient for global optimization in the continuous domain. At each generation, it employs mutation, crossover, and selection operations in order to progress its population closer and closer to the global optimal. The DE method has been shown to have superior performance when compared to other algorithms in a number of different study papers [10, 12, 13]. In spite of the benefits that have been discussed so far, the original DE and many of its variations are nevertheless plagued by a number of problems. DE

does not always lead to a convergent state that is optimal on a global scale. It is simple to become stuck in a local optimum, which might lead to a reduction in optimizing accuracy or even an unsuccessful attempt [14]. In DE, it's possible that the population isn't evenly distributed around the search space, and that some people are stuck in local solutions. It is possible that further generations will be necessary in order to converge toward an optimum or near-optimal solution [15]. DE has been demonstrated to have significant flaws, particularly if the global optimum should be determined by employing a restricted number of fitness function evaluations, which is one of DE's main limitations. It is effective at discovering the area of global minimum and exploring the search space, but it is sluggish when it comes to exploiting the solution [16].

One definition of chaos describes it as an irregular motion or a behavior that seems uncontrolled but is really controlled by predetermined factors. Systems that are chaotic are sensitive to even minute changes in their starting conditions, and these changes may have a profound impact on the results. It is particularly sensitive to the beginning circumstances, and this sensitivity is the quality that is often referred to as the instability in the so-called butterfly effect or in the sense of Liapunove [17]. An effective method for preserving the population variety in search algorithms may be derived from the chaotic systems' innate properties thanks to the nature of these systems.

The process of clustering is considered to be both one of the most significant and difficult of all classification techniques. The ability to dependably locate actual natural groups within the data set is essential to the success of any clustering effort. By bringing cluster centers to the populations, a fuzzy c-means clustering method, which is a soft clustering technique, has been brought into DE in order to assist in tracking the development of the search process. The technique of grouping a collection of items into groups or clusters based on their similarities is referred to as fuzzy c-means clustering. This helps to speed up the optimization search in DE.

As a result, the purpose of this study is to make use of fuzzy c-means clustering and chaotic approaches in order to overcome the challenges presented by the original DE. Instead of using random sequences, chaotic sequences have been used, and the results have been used in a way that is both highly fascinating and somewhat successful in order to avoid the new strategy from prematurely converging. In the meanwhile, fuzzy c-means clustering functions as numerous multi-parent crossover operators to make the algorithms converge more quickly by effectively using the information contained within the population. The following is the structure of the paper: In the second half of this paper, a short literature review pertaining to the development of the novel optimization model is presented. In sections 3 and 4, an in-depth examination of the newly suggested optimization model provides the reader with an overall view of the framework. In section 5, a numerical experiment and result comparisons are used to illustrate how well the newly created model performs. In the very final part of this article, a discussion of the conclusions is included..

Literature review

2.1 The Distribution of Resources

Within the constraints of the needed project time and working under the premise that there is a limitless supply of resources, the goal of the resource-leveling issue is to bring down the peak demand for those resources while also evening out the consumption on a daily basis. Therefore, the problem of resource leveling may be formulated as an optimization issue in which the following cost function must be reduced in order to get the best possible solution [9, 18].]:

$$f = \sum_{i=1}^{T} (y_i - y_u)^2 \quad (1)$$

where T signifies the period of the project, yi represents the entire resource needs of the activities conducted at time unit I and yu represents a uniform resource level supplied by. yi represents the total resource requirements of the activities performed at time unit i.

$$y_u = \frac{\sum_{i=1}^{T} y_i}{T} \quad (2)$$

According to Son and Skibniewski [9], Eq. (1) can be rewritten as follows

$$f = \sum_{i=1}^{T} y_i^2 - 2y_u \sum_{i=1}^{T} y_i + y_u^2 \quad (3)$$

Since activity duration and rate of resource for each activity are fixed, y_u and $\sum_{i=1} y_i$ are constant. Thus, the cost function can be expressed as

$$f = \sum_{i=1}^{T} y_i^2 \quad (4)$$

In its most basic form, Equation (4) is analogous to the minimum moment of the resource histogram around the time axis, as was discussed in earlier works [18, 19]. In addition, the goal function of the resource-leveling issue requires some adjustment in order to be fully resolved. This is due to the fact that the optimization process might potentially provide several scheduling solutions, or, to put it another way, resource profiles that have the same minimal moment of resource demand [9]. Despite the fact that the values of the cost function are same, the resource fluctuations may be somewhat different. Therefore, in order to determine which resource profile is the most desirable, it is necessary to take into consideration the differences in consumption levels that occur across successive time periods [20] and the point at which resource demand is at its highest [9]. A revised goal function for the resource-leveling optimization model is offered further on in the study..

2.1 Chaos Approach

Chaos theory is a scientific theory describing erratic behavior in certain nonlinear dynamical systems. Chaotic mappings can be considered traveling particles within a limited range occurred in a deterministic nonlinear dynamic system. There is no definite regularity for such a traveling path. Such a movement is very similar to a random process, but extremely sensitive to the initial condition [21]. Chaotic sequences have been proven easy and fast to generate and store, there is no need for storage for long sequences [15]. Moreover, these sequences are deterministic and reproducible. Many researchers have adopted chaotic sequences instead of random sequences [22, 23].

The one dimensional logistic map is one of the simplest systems with density of periodic orbits

$$X_{n+1} = \mu(1 - X_n)$$

In this equation, X is the n^{th} chaotic number where n denotes the iteration number. Obviously, $X_n \in (0,1)$ under conditions that initial $X_0 \in (0,1)$ and that $X_0 \notin \{0.0, 0.25, 0.5, 0.75, 1.0\}$. The variation of control parameter μ in Eq. (5) will directly impact the behavior of X greatly. The domain area of control parameter μ has often been defined as $[0, 4]$. In the experiments $\mu = 4$ has been used.

The logistic map that generate chaotic sequences in DE, named CDE which ensures the individual in population to be spread in the search space as much as possible for population diversity used in experiments. Incorporating chaotic map into DE is proven to enhance the global convergence by escaping the suboptimal solution. Figure 1 shows the main steps of generating chaotically population.

2.2 Fuzzy c-means Clustering

Clustering is a procedure that divides an existing collection of items into smaller subgroups or clusters on the basis of their similarities to one another. The goal is to partition the collection of data in such a manner that items that belong to the same cluster are as comparable to one another as is reasonably feasible, while objects that belong to separate clusters are as unlike to one another as is reasonably possible. Clustering algorithms can be broken down into two primary categories: crisp (or hard) clustering procedures, in which every piece of data is designated to exactly one cluster, and fuzzy clustering techniques, in which every data point is considered to be a member of each cluster to varying degrees depending on the algorithm [24]. The research literature presents a number of different clustering methods. In this particular investigation, the fuzzy c-means (FCM) clustering method [25] is used.

It was possible for the FCM clustering approach used in DE, which was given the term FDE, to simply carry out an efficient convergence of DE. The FCM was included in this investigation with the purpose of tracing the primary current of population migration over the course of DE development.

. Each cluster centers could be treated approximately as one of the items in the main stream of evolution, and replaced for population as candidate individuals. The FDE algorithm is illustrated in Figure 2. Where m is clustering period, NP is the population size, and k, the number of centroid [26], is an integer number from [2, NP] .

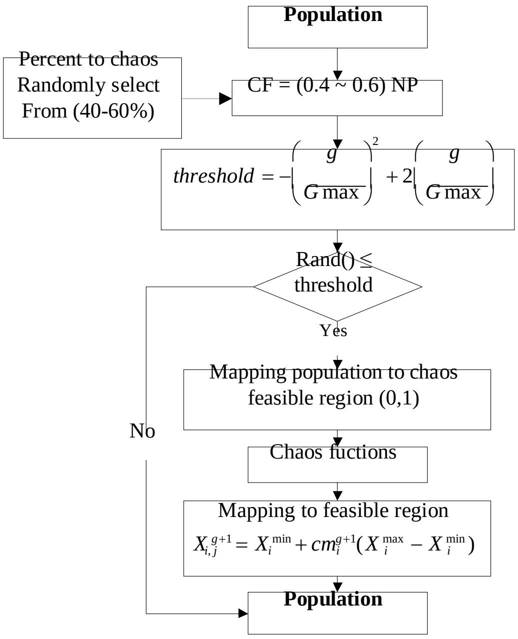


Figure 1 Chaotic approach

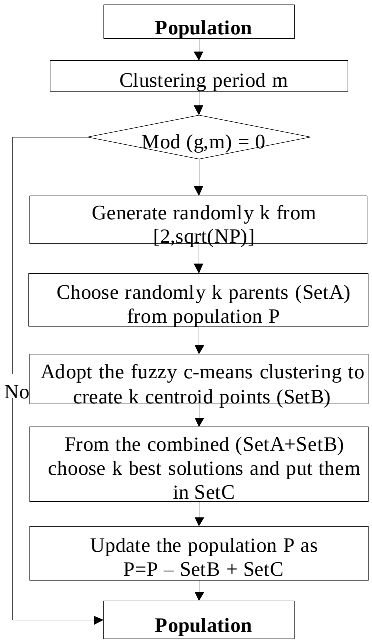


Figure 2 Fuzzy c-means clustering algorithm

2. Fuzzy c-means Clustering Chaotic-based Differential Evolution (FCDE)

The suggested method for FCDE optimization is broken down into its component parts and discussed in this section. Within the FCDE-RL framework, the FCDE serves as the primary search engine. It has been brought to our attention that our method was built on the basis of conventional Differential Evolution [10, 11]. This was accomplished by combining the traditional DE with fuzzy c-means clustering and chaotic approaches. The chaos strategy successfully leverages the whole of the search space and supplies the essential variation in the DE population. As a direct result of this, the process of finding the global optimum requires an increased amount of time and iterations. By incorporating the cluster centers, the fuzzy c-means clustering approach, on the other hand, helps the algorithm converge more quickly. These moving centers give a direction for the search of the global optimal, which improves the search algorithm's overall efficiency. The FCDE model takes advantage of the inherent qualities of both the chaos algorithm and fuzzy clustering, and then integrates those features with differential evolution. This allows the model to improve the overall search capabilities of DE when it comes to locating the best solutions for a specific search space. The suggested algorithm's big picture may be seen in the following illustration:

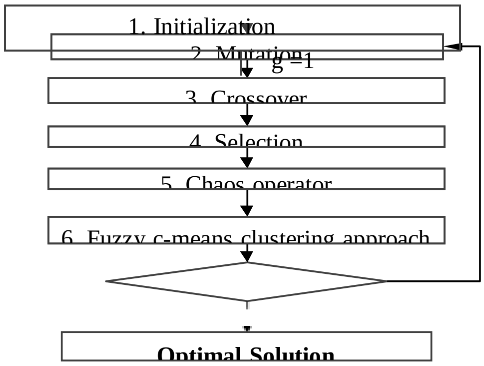


Figure 3 Fuzzy Clustering Chaotic based Differential Evolution (FCDE)

3.1 Initialization

FCDE commences the search process by randomly generating population size NP, Maximum of generation $G_{\max}$ number of D-dimensional parameter vectors $X_{i,g}$ where $i = 1, 2, ..., NP$ and g indicates the current generation. In the original DE algorithm, NP does not change during the optimization process [11]. Moreover, the initial population (at g = 0) is expected to cover the entire search space uniformly. Hence, we can simply generate these individuals as follow:

$$X_{i,0} = LB + rand[0,1]*(UB - LB) \quad (6)$$

Where x is the decision variable i at the first generation. $rand[0,1]$ denotes a uniformly distributed random number between 0 and 1. *LB* and *UB* are two vectors of lower bound and upper bound for any decision variable.

3.2 Mutation

The present population is used to generate a mutant vector for each target vector by selecting three vectors at random from the population. It is important to keep in mind that the size of the mutation scale factor, denoted by the letter F, has an effect on the search step of the mutation operator. The mathematical representation of this procedure is as follows::

$$V_{i,g+1} = X_{r1,g} + F(X_{r2,g} - X_{r3,g}) \quad (7)$$

where *r1*, *r2*, and *r3* are three random indexes lying between 1 and *NP*. These three randomly chosen integers are also selected to be different from the index *i* of the target vector. *F* denotes the mutation scale factor, which controls the amplification of the differential variation between $X_{r2,g}$ and $X_{r3,g}$. $V_{i,g+1}$ represents the newly

3.3 Crossover

The goal of the crossover stage is to increase the genetic diversity of the existing population by swapping target vector components with mutant vector components. During this step, a new vector that will be used in the experiment is created and given the name trial vector. The term "offspring" may also be used to refer to the trial vector. The trial vector may be constructed as shown in the following example::

$$U_{j,i,g+1} = \begin{cases} V_{j,i,g+1}, & if \ \ rand_j \leq Cr \\ X_{j,i,g}, & if \ \ rand_j > Cr \end{cases}$$

where the trial vector is denoted by Uj,i,g+1. The value of j indicates the position of the element in any vector. randj is a number that is completely random and lies between 0 and 1. The user is responsible for calculating the crossover probability, which is denoted by the symbol Cr. rnb(i) is an index that is picked at random from the range of 1,2,..., NP, and it ensures that at least one parameter from the mutant vector is taken into account. ($V_{j,i,g+1}$)

3.4 Selection

In this stage, the trial vector is compared to the target vector [11]. If the trial vector can yield a lower objective function value than its parent, then the trial vector replaces the position of the target vector. The selection operator is expressed as follow:

$$X_{i,g+1} = \begin{cases} U_{i,g} & if \quad f(U_{i,g}) \le f(X_{i,g}) \\ X_{i,g} & if \quad f(U_{i,g}) > f(X_{i,g}) \end{cases} \quad (9)$$

3.5 Chaos Operator

If the probability condition is satisfied, a percentage of the population is selected to do chaos. Mapping population to chaotic feasible region $(0,1)$ and performs the logistic map following equation (5). Afterwards, map the chaotic variables to feasible region according to equation (10):

$$X_{j,i}^{g} = X_{j}^{\min} + cm_{k}^{j}(X_{j}^{\max} - X_{j}^{\min}) \quad j = 1,2,\cdots,D \quad (10)$$

where $cm_k^{\,j}$ are chaotic variables according to chaotic formula.

3.6 Fuzzy c-means clustering approach

Initially, the period of the clustering operator specified in the algorithm is 10. Consequently, the number of

clusters defined randomly in range of [2, $\sqrt{NP}$]. The corresponding centroids of each cluster are added to the population as feasible solutions.

3.7 Stopping Condition

Once the halting requirement has been satisfied, the optimization process will come to an end. This condition's kind is up to the discretion of the user. As a standard practice, the halting condition may be determined by either the maximum generation (Gmax) or the maximum number of function evaluations (NFE). When the optimization procedure is complete, the user will be given easy access to the final optimum solution..

3. Resource balancing via fuzzy c-means clustering and chaotic-based differential evolution

In the following paragraphs, the FCDE-RL optimization model will be discussed in detail (see Figure 4). It has been brought to our attention that the FCDE-RL was built using the FCDE as the searching engine as its foundation. This optimization model's goal is to reduce the amount of daily variation in resource use as much as possible while maintaining the same overall project length.

In this investigation, we look at the possibility that resource leveling might be achieved by reducing, as much as possible, the variations that occur between the levels of resources that are required and those that are considered optimally uniform. The model necessitates the input of project information, such as the activity connection, activity length, and resource demand. In addition, the user is responsible for providing the search engine with the appropriate parameter settings. These settings include the maximum number of searching generations (Gmax), the population size (NP), the chaotic percentage (CF), and the period clustering (m). With these inputs, the scheduling module will be able to carry out the computation process and get a schedule based on the critical path method (CPM), as well as the early start and late start times for each activity. The model is able to function autonomously and does not need any input from a person since it has all o f the information that it require s

.

Parameter Generation
Mutation
Crossover
Selection

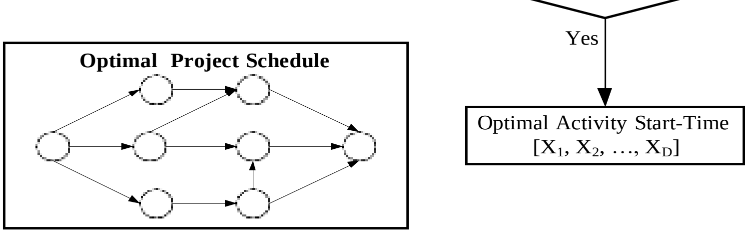


Figure 4 Fuzzy Clustering Chaotic based Differential Evolution for Resource Leveling (FCDE-RL)

An initial population of possible solutions is generated using a uniform random generator before the search process can even begin. This is done so that the results of the search are more accurate. A solution to the issue of resource allocation may be described as a vector containing D components in the following way::

$$X = [X_{i,1}, X_{i,2}, \ldots, X_{i,D}]$$

where D is the number of decision variable of the problem at hand. It is obvious that D is also the number of activities in the project network. The index *i* denotes the i^{th} individual in the population. The vector X represents the start time of D activities in the network. Since original DE operates with real-value variables, a function is employed to convert those activities' start times from real values to integer values within the feasible domain.

$$X_{i,j} = Round(LB(j) + rand[0,1] \times (UB(j) - LB(j))) \quad (12)$$

where $X_{i,j}$ is the start time of activity *j* at the individual i^{th}. *rand[0,1]* denotes a uniformly distributed random number between 0 and 1. *LB(j)* and *UB(j)* are early start and late start of the activity *j*.

The search engine (FCDE) takes into account the result obtained from scheduling module and shifts noncritical activities within their float times to seek for an optimal project schedule. In the research, the following objective function and constraints are employed:

$$f = \alpha \sum_{k=1}^{T} (y_k)^2 + \beta \sum_{k=1}^{T-1} y_{k+1} - y_k$$

Subject to

$$ST_i - ES_i \leq TF_i \; ; \; ST_i \geq 0 \; ; \; i = \quad (11)$$

where T signifies the total amount of time that will be spent on the project and yk is the total amount of resources that will be needed for the activities that will be carried out during time unit k. The difference in resource use between two successive time periods may be measured using the formula (yk+1 - yk). During the course of the project's execution, the resource demand will reach its highest point, denoted by ymax. Weighting coefficients are denoted by the symbols,, and. The start time of activity I is denoted by the acronym STi. Both the early start and the total float of activity I are denoted by the notation ESi and TFi, respectively. D represents the total number of activities taking place throughout the network.

When the searching procedure comes to an end, the best possible option will have been found. After that, the timeline for the project and the resource histogram that goes along with it are developed based on the best possible time to begin activities..

Experimental Results

In this part, the capabilities of the recently constructed FCDE-RL model are shown by using a building project that was taken from Sear et al. [27]. There are a total of 44 activities included in the project, and the length of the project as a whole is estimated to be 70 days (see Table 1). Within the scope of this investigation, the resource of particular importance is personnel. Figure 5 illustrates the resource profile of the project prior to the use of the resource-leveling method.

Table 1 Project information

Activity ID	**Duration**	**Predecessors**	**Daily Resource Demand**	**Early Start (ES)**	**Late Start (LS)**
1	0		0	0	0
2	10	1	5	0	0
3	5	1	2	0	9
4	15	1	3	0	3
5	3	1	2	0	12
6	10	1	2	0	8
7	15	2	6	10	10
8	7	3	10	5	14
9	3	5	6	3	22
10	3	5	2	3	15
11	2	5	2	3	16
12	3	9, 10, 11	6	15	18
13	2	10	1	6	19
14	2	8, 12	5	18	21

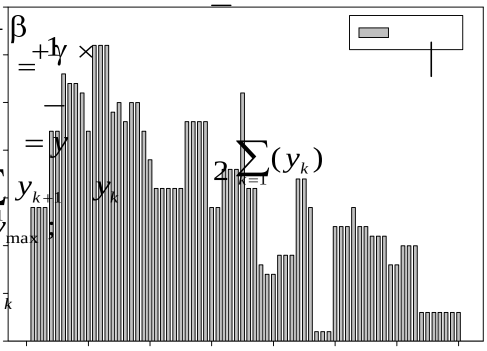
15	3	12, 13	2	18	21
16	1	14	6	20	23
17	1	15	7	21	24
18	1	16	7	21	24
19	4	7, 9, 17, 18	13	25	25
20	2	15, 18	9	22	30
21	2	19	4	29	29
22	1	20	6	24	32
23	3	21	8	31	31
24	1	22	3	25	33
25	4	23, 24	8	34	34
26	2	25	7	38	38
27	25	6	10	10	18
28	3	23	6	34	52
29	3	23	2	34	40
30	3	26	9	40	40
31	3	30	10	43	52
32	3	30	3	43	46
33	2	27, 29, 30	4	43	43
34	0	32	0	46	49
35	4	33	1	45	45
36	3	34, 35	12	49	49
37	3	36	12	52	52
38	3	28, 31, 37	3	55	57
39	5	28, 31, 37	8	55	55
40	1	36	2	52	59
41	3	38, 39, 40	10	60	60
42	1	41	3	63	63
43	6	42	3	64	64
44	0	43	0	70	70

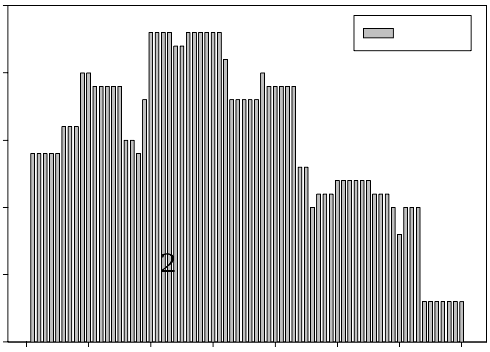
5.1 Optimization result of FCDE-RL

In this part of the article, the FCDE-RL model is used to cut down on the considerable resource swings. Table 2 displays the parameter settings that were used for the FCDE optimizer. Figure 6 presents the revised resource profile for the project that was produced by FCDE-RL after its optimization. The ideal solution, as well as the optimal starting times for the activities, are shown in Table 3. The following is a listing of the best outcomes that may be achieved with the new model::

Fitness = 9486, M_x = 9201, RD_{max} = 23, RV_{max} = 7, and *CRV* = 55.

Where: $Fitness = \alpha \times M_x + \beta \times RD_{max} + \gamma \times RV_{max}$; $M_x = \sum_{k=1}^{T} (y_k)^2$; $RD_{max} = y_{max} - \bar{y}$; $\bar{y} = \frac{1}{T}\sum_{k=1}^{T} y_k$;





$$RV_{\max} = \max[\,|y_2 - y_1|, |y_3 - y_2|, \ldots, |y_T - y_{T-1}|\,] \; ; \; CRV = \sum_{k=1}^{T-1} (|y_{k+1} - y_k|)$$

Table 2 FCDE-RL's parameter setting

Input parameters	Notation	Setting
Number of decision variables	*D*	44
Population size	*NP*	8x*D*
The crossover probability	*CR*	0.9

Percentage of population to chaos	*CF*	40-60%
Period clustering	*m*	0.1
Number of centroid in clustering	*k*	$[2,\ NP]$
Maximum generation	G_{max}	3000
Weighting coefficient 1	α	1
Weighting coefficient 2	β	1
Weighting coefficient 2	γ	10

Table 3 Optimal Start Time (ST) for all activities found by FCDE-RL

Activity ID	Optimal ST	Activity ID	Optimal ST	Activity ID	Optimal ST	Activity ID	Optimal ST
1	0	**12**	15	**23**	31	**34**	48
2	0	**13**	15	**24**	31	**35**	45
3	0	**14**	19	**25**	34	**36**	49
4	0	**15**	18	**26**	38	**37**	52
5	0	**16**	23	**27**	18	**38**	55
6	0	**17**	22	**28**	43	**39**	55
7	10	**18**	21	**29**	37	**40**	58
8	8	**19**	25	**30**	40	**41**	60
9	5	**20**	29	**31**	46	**42**	63
10	15	**21**	29	**32**	43	**43**	64
11	3	**22**	24	**33**	43	**44**	70

5.1 Result comparisons

Table 5 displays a comparison of the findings obtained using FCDE-RL with the project management software Microsoft Project 2007, which may be found here. When compared to the performance of the commercial software in terms of Mx, RDmax, RVmax, and CRV, it is evident that the performance of the new model is noticeably superior. This indicates that the new model has significantly mitigated the fluctuations in resource availability.

Table 4 Result comparison between FCDE-RL and Microsoft Project 2007

Methods	M_x	RD_{max}	RV_{max}	***CRV***
FCDE-RL	**9201**	**23**	**7**	**55**
Microsoft Project 2007	9717	24	14	125

Standard DE (DE) [28], Genetic Algorithm (GA), and Particle Swarm Optimization are the three distinct algorithms that are employed for performance comparison in this study. The purpose of this study is to better validate the performance of the suggested model (FCDE-RL) (PSO). The optimization performance of each algorithm is evaluated based on the best result discovered (best), the average result (avg), the standard deviation (std), and the worst result (worst) after 20 iterations of running the algorithm. This helps to determine how reliable and accurate each method is (see Table 5).

According to what can be shown in Table 5, the performance of the recently constructed model is comparable to that of other models in terms of its accuracy and stability. The suggested method obtains the best results possible in each of the metrics that are used to quantify performance. The moment of the resource histogram, the highest resource demand, and the variance of resource across successive periods are all effectively reduced thanks to FCDE-efforts. RL's The new model is shown to be more accurate and stable than previous algorithms due to the fact that the average and standard deviation of the results acquired from FCDE-RL are both less than those obtained from the other methods.

Table 5 Result comparison between FCDE-RL and benchmarked algorithms

Performance Measurement		**PSO**	**GA**	**DE1**	**DE2**	**DE3**	**FCDE-RL**
Fitness	*Best*	9591.0	9579.0	9548.0	9488.0	9488.0	**9486.0**
	Avg	9682.9	9609.3	9610.6	9508.5	9508.1	**9494.5**
	Std	79.8	14.1	44.1	17.1	10.2	**7.5**
	Worst	9940.0	9630.0	9713.0	9566.0	9522.0	**9504.0**
M_x	*Best*	9266.0	9251.0	9235.0	**9201.0**	**9201.0**	**9201.0**
	Avg	9320.3	9278.5	9280.8	9219.1	9216.9	**9206.5**
	Std	56.5	12.7	26.8	11.3	10.0	**7.6**
	Worst	9513.0	9303.0	9323.0	9251.0	9231.0	**9221.0**
RD_{max}	*Best*	24.0	**23.0**	**23.0**	**23.0**	**23.0**	**23.0**
	Avg	27.4	23.8	24.9	**23.0**	23.4	**23.0**
	Std	2.6	0.7	1.7	**0.0**	0.5	**0.0**
	Worst	32.0	26.0	29.0	**23.0**	24.0	**23.0**
RV_{max}	*Best*	**7.0**	**7.0**	**7.0**	**7.0**	**7.0**	**7.0**
	Avg	8.5	9.3	9.1	7.2	7.2	**7.0**
	Std	0.9	1.2	1.0	0.6	0.6	**0.0**
	Worst	10.0	12.0	10.0	9.0	9.0	**7.0**
CRV	*Best*	61.0	77.0	68.0	**51.0**	**51.0**	**51.0**
	Avg	89.1	92.8	81.3	59.3	57.2	**56.3**
	Std	12.1	9.0	10.8	9.9	3.5	**2.8**
	Worst	110.0	109.0	109.0	85.0	**65.0**	**65.0**

Conclusions

In this study, we describe the usage of FCDE as a solution to the issue of resource leveling. The merging of two distinct algorithms, fuzzy clustering and chaos, has shown to be an useful method for removing the shortcomings of the original DE. The unpredictability of the chaos algorithm boosted the population variety and prevented it from being stuck at a local optimum, while the fuzzy c-means clustering improved the convergence speed of the search method supplied by the shifting cluster centers.

The FCDE-RL algorithm has been shown to be capable of producing accurate and consistent results via a series of experiments and result comparisons. When it comes to the resolution of big and complicated optimization issues in construction management, the improved performance of FCDE provides an alternative option.

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