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Fuzzy Evolutionary Algorithm in Construction Project for Valuation

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Abstract: - Construction project valuation refers to the process of determining the economic value or worth of a construction project. This assessment is crucial for various stakeholders involved in the construction industry, including investors, lenders, developers, and contractors. Clustering algorithms has emerged as an important data mining technique for pattern recognition, data analysis and dimensionality reduction. Clustering is usually used in all fields to merge the same feature objects into a single group. The clustering method is incorporated with search algorithms to search the dataset from the databases. For large databases, there is a need of good clustering algorithm with high accuracy. Despite its high performance, the existing methods show some limitations. This paper focused on optimize the clustering method with a search structure for large multidimensional databases with dynamic indexes for the effective validation of construction projects. In the construction project validation to improve the clustering methods using Evolutionary Constrained Differential Optimization (ECDO) and Distributed Weighted Fuzzy C-Means algorithm to improve clustering performance than the centralized clustering approaches. The proposed methodology includes ECDO which presents new cluster tree indexing approach with cluster speed improvement in the validation of the construction projects. Distributed Fuzzy Possibilistic C-Means algorithm is proposed in improvement of cluster centre to overcome coincidence cluster problems. The comparative analysis stated that proposed ECDO model exhibits ~6% reduced memory utilization ~11% reduced scalability and ~8% minimized selectivity than the conventional WPCM model.

Keywords: Data processing, Construction Projects multi-dimensional data, Fuzzy C-means, clustering, Optimization.

I. INTRODUCTION

Construction projects are multifaceted endeavors that encompass a spectrum of activities, from conceptualization to completion. These projects can encompass diverse categories, such as residential, commercial, infrastructure, and industrial developments [1]. The various phases of a construction project, from initiation and planning to design, procurement, construction, and eventual closure, demand meticulous planning and execution. A multitude of stakeholders, including owners, design professionals, contractors, subcontractors, suppliers, regulatory agencies, and the local community, play integral roles in shaping these projects. Challenges and risks, ranging from cost overruns and delays to quality control and environmental impact, underscore the complexity of the construction industry [2]. However, ongoing technological advancements, like Building Information Modeling and sustainability practices, are reshaping the sector, making it more efficient, safe, and environmentally friendly. As a significant driver of urban development and an emblem of human achievement throughout history, construction projects remain integral to the growth and progress of societies worldwide. Construction projects represent intricate undertakings that span a wide spectrum of industries and purposes, from residential and commercial buildings to critical infrastructure and environmental initiatives [3]. These projects typically follow a well-defined series of phases, from initial concept and planning to design, procurement, execution, and eventual handover. Within this dynamic framework, a plethora of stakeholders including project owners, design professionals, contractors, subcontractors, suppliers, regulatory bodies, and the broader community all contribute their expertise and interests to the endeavor [4].

One of the key challenges in construction projects is optimization – how to best allocate resources, time, and capital to ensure that a project is completed efficiently, within budget, and to the highest quality standards. Optimization models play a vital role in achieving these objectives. They involve the utilization of mathematical and computational techniques to address complex decision-making processes [5]. These models help in determining the most cost-effective allocation of resources, scheduling of tasks, and risk management strategies. For example, linear programming, critical path analysis, and simulation modeling are commonly used methods. By implementing optimization models, construction projects can minimize cost overruns, reduce delays, enhance quality control, and improve overall efficiency [6]. As the construction industry embraces these advanced techniques, it stands to further

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streamline its operations and contribute to the development of more sustainable, cost-effective, and resilient structures, ultimately benefiting both the industry and the communities it serves.

Data mining plays a pivotal role in construction projects by harnessing the power of data to enhance decision-making, efficiency, and overall project success [7]. In the realm of construction, data mining involves the extraction of valuable insights and patterns from the extensive datasets generated throughout a project's lifecycle. These datasets encompass project plans, schedules, budgets, material specifications, equipment usage, and even environmental factors. Data mining aids in risk management by identifying potential issues or delays, allowing project managers to proactively address them [8]. It can predict when certain equipment require maintenance or replacement, optimizing resource allocation and reducing downtime. By analyzing historical data, construction firms can refine cost estimates and project timelines, reducing the likelihood of budget overruns and schedule delays. Moreover, data mining contributes to safety improvements [9]. It can detect patterns in accident data and near misses, helping project teams implement preventive measures and enhance safety protocols. Additionally, it assists in quality control by identifying deviations from expected outcomes, thus ensuring that construction standards are met.

As the construction projects with data-driven insights, transforming the industry into a more efficient, cost-effective, and safe endeavor. By leveraging this technology, construction companies can make more informed decisions, mitigate risks, and ultimately deliver successful projects while optimizing resource allocation and sustainability. Data mining has become an important application of information technology and an association of different interrelated areas and application domains [10]. Data mining is a process of identifying or discovering interesting patterns from enormous volumes of information. The key steps in a search process are data cleaning, data integration, data selection, data transformation, and pattern discovery, among other things [11]. The data should have a proper meaning for the data mining process. It can be used with data from a database; advanced data types, transactional data, and data from a data warehouse Some advanced data types include time-related, data streams, spatial data, text and multimedia data, graph, networked data, and web data [12]. Diverse applications produce a wide range of novel data types, including simple data objects, complex data objects, stable data, unstructured data, and structured data. Based on the various objectives of data mining, it is unrealistic to expect a single data mining system to produce an efficient mining result for all of the aforementioned data types [13]. A significant area of recent research for improved pattern search in a complex data management environment is the development of better mining tools for an efficient data mining process. Using different network connections different sources of data are connected over the internet [14]. Multidimensional data model consists of Logical cubes, measures, dimensions, hierarchies and attributes. Naturally the data model is laid to be simple since it defines objects that represent real world entities [15]. Data analysts are aware of their interest in examining or evaluating, finding out which dimensions and attributes make the data based on the hierachies. Integrating data mining techniques along with data warehousing is gaining momentum due to the fact that both functionalities supplement each other in extracting knowledge from large volumes of datasets [16]. Most approaches look forward in using data mining as a front end technology to mine data warehouses. When it comes to the creation of data warehousing facilities, modifications to mining methods have recently been made. Multidimensional data are the subject of techniques like clustering that are used to enhance the knowledge discovery process [17]. Regarding the creation of multidimensional schema, some fundamental issues remain unsolved. The selection of factual and informative dimension variables is extensive.

Typically, clustering is used to combine similar feature objects into a single group in all fields. In order to search the dataset from the databases, the clustering method is already incorporated with search algorithms. A reliable and accurate clustering algorithm is required for large databases. Clustering-based search algorithm [18]. The approach has some drawbacks despite its high performance. Even though clustering yields good results, clustering tree methods consume a lot of computational power to perform with accuracy and time. As a result, decided to use the clustering technique and a search structure with dynamic indexes for large multidimensional datasets. Advanced database systems have emerged in recent years. They are essential due to the interest for capacity, the executives and recovery of a lot of information in application regions, for example, Satisfied based Recovery, Electronic Commercial centers and Choice Help Applications overall. Users of advanced database systems, in contrast to users of conventional database systems, place a strong emphasis on multi-criteria optimization and similarity search. The identified four requirements based on a comprehensive analysis of advanced database system-typical objects and properties. This paper proposed an Evolutionary Constrained Differential Optimization (ECDO) for the clustering process to optimize the features in the distributed environment. The ECDO model uses the C-means clustering process for the computation of variables.

II. RELATED WORKS

Clusters for specific parameters are provided by some formats, while others provide a layer of clusters. The K-Means calculation, Linkage techniques, and diagram hypothetical calculations are the most generally utilized bunching calculations. Data mining is a vital tool in the construction industry, where it extracts valuable insights from vast datasets, helping improve decision-making, efficiency, and overall project success. By analyzing data from project plans, budgets, schedules, and environmental factors, data mining enhances risk management by identifying potential issues and delays. It also aids in resource allocation by predicting maintenance needs, refines cost estimates, and contributes to safety improvements by detecting accident patterns. This technology empowers construction projects with data-driven insights, making them more efficient, cost-effective, and safe, ultimately delivering successful and sustainable results.

[19] provides a number of graph-theoretical algorithms based on the minimum spanning tree. By distinguishing and eliminating conflicting edges from the MST and framing associated parts of edges to get bunches, the calculation gives a strategy to determine a MST for a specific example. Non-spherical clusters and clusters with shifting point densities are two examples of datasets that this method works well with. However, special patterns are required to locate inconsistent edges in more complicated circumstances. When there are two identical clusters with little difference in point densities, for instance, the sparse cluster will have more inconsistent edges. In addition, in order to select the appropriate heuristic for obtaining inconsistent edges, advanced knowledge of the cluster's shapes is required. It go beyond just the two dimensions. In [20], it was demonstrated to produce superior results for a variety of cluster types. However, these methods needed to be developed for two-dimensional data because of the difficulties with computation in higher dimensions. These are partitional techniques. The most frequently used hierarchical algorithms are agglomerative hierarchical clustering algorithms like the complete linkage method and the wards method.

An overview of PSO and its various types' applications to clustering difficulties was provided in [21]. An advanced PSO algorithm for clustering multidimensional data is the Subtractive Clustering Challenges Based on Boundary Restricted Adaptive Particle Swarm Optimization (SC-BR-APSO) algorithm. Evaluation and analysis of various algorithms, including K-Means, PSO, and others, are studied. nine distinct data sets, the hybrid subtractive +PSO algorithm that was proposed, and The management of multidimensional data clustering with the lowest error rate and highest convergence rate is the objective of the SCBR-APSO algorithm. A brand-new hybrid sequential clustering strategy that employs the K-Means algorithm for sequential data clustering was developed in [22]. Efficiency is enhanced by avoiding the issue of stagnation. In order to compare results from four distinct data sets, they are being tested. Deterrent algorithms are used for assessment, whereas this algorithm produces effective results. Mehdi and co. The PSO and K-Means algorithms serve as the foundation for's cooperative algorithm. The proposed algorithm makes use of both PSO's global search capacity and K-Means' local search capacity. The proposed algorithm outperformed the PSO, K-Means, and KPSO hybrid algorithms when tested and compared to them.

According to [23], the efficiency of clustering algorithms increases with the number of overlaps between clusters in a data set. In order to avoid overlapping, a novel clustering technique known as a Fuzzy Multi-Objective Particle Swarm Optimization Framework (FMOPSO) was developed. This is able to produce better results than the clustering algorithms that are currently available. The algorithm's efficacy has been evaluated through numerous statistical tests on a variety of numerical and categorical real-world data sets. An algorithm that can combine methods of weighted dimensionality reduction with AUTO-PSO clustering. The objective is to simplify the data sets and enhance the auto PSO clustering procedure. During operation, better improvement is achieved. The precision with which dimension space is utilized by clustering algorithms is comparable to that of clustering algorithms. A novel clustering particle swarm optimization based on the gauss chaotic map was proposed in [24]. The Gauss chaotic map provides the crucial distribution necessary to achieve equilibrium in the capacity for exploration and exploitation during the search process. Due to their unconventionality, it is simple and quick to acquire irregular seed processes and further increase PSO display. The study links the various clustering algorithms to six data sets. Due to the proposed algorithm's functionality, the results are superior to those of the existing algorithms, as shown by the findings.

III. CONSTRUCTION PROJECTS ECDO

The research method for data mining in construction projects focuses on optimizing clustering algorithms to address the unique challenges associated with large multidimensional databases and dynamic indexes. Clustering, a fundamental data mining technique, is employed to group similar objects with common features, but for construction projects, where datasets can be extensive and frequently updated, the need for accurate and efficient clustering methods is paramount. To achieve this, the research employs two innovative techniques: Evolutionary Constrained Differential Optimization (ECDO) and the Distributed Weighted Fuzzy C-Means algorithm. ECDO introduces a novel cluster tree indexing approach that enhances clustering efficiency by incorporating evolutionary algorithms to handle large datasets with dynamic indexes, while the Distributed Weighted Fuzzy C-Means algorithm improves cluster center calculation, mitigating issues related to coincident clusters. By combining these methods, the research aims to significantly enhance clustering performance, resulting in improved pattern recognition, data analysis, and dimensionality reduction in the construction industry, where real-time data management and decision-making are of utmost importance. This methodology seeks to overcome the limitations of existing clustering approaches and offer more accurate and efficient solutions for data mining in construction projects. The mentioned techniques (ECDO and Distributed Weighted Fuzzy C-Means) would require a significant amount of space and mathematical complexity. In clustering, the primary objective is to minimize the distance between data points within the same cluster while maximizing the distance between clusters. The proposed ECDO model uses the K-means clustering objective function as represented in equation (1):

$$J = \sum_{i=1}^{K} \sum_{j=1}^{N_k} \left| x_j^{(i)} - c_i \right|^2 \tag{1}$$

where K is the number of clusters, N_k is the number of data points in cluster k, $x_j^{(i)}$ is the j-th data point in cluster i, and c_i is the centroid of cluster i. ECDO integrates evolutionary algorithms, like Genetic Algorithms (GA), to optimize clustering. GAs include operations like selection, crossover, and mutation, which evolve a population of candidate solutions (cluster configurations) to find the optimal solution. Deriving the exact equations for ECDO involves defining the genetic operators (e.g., mutation, crossover) and fitness functions that guide the evolution of candidate cluster configurations. These equations are highly specific to the algorithm and require in-depth knowledge of genetic algorithms and clustering.

3.1 Distributed Weighted Fuzzy C-Means Algorithm:

Fuzzy C-Means (FCM) aims to minimize the objective function, which incorporates the degree of membership of data points in each cluster computed using equation (2)

$$J = \sum_{i=1}^{N} \sum_{j=1}^{C} \mu_{ij}^{m} \left| x_j - v_i \right|^2 \tag{2}$$

In FCM, the membership degree of a data point to a cluster is calculated using the equation (3)

$$\mu_{ij} = \left(1 / \sum_{k=1}^{C} \left(\frac{|x_j - v_i|}{|x_j - v_k|} \right)^{\frac{2}{m-1}} \right)^{-1} \tag{3}$$

To derive the equations for the Distributed Weighted Fuzzy C-Means algorithm, one would need to detail how the cluster centers (v_i) are updated and how the membership degrees (μij) are adjusted in a distributed manner. These derivations can be complex and depend on the specific algorithm used. ECDO incorporates evolutionary algorithms, such as Genetic Algorithms (GA), into the optimization process. Genetic Algorithms use principles of natural selection, crossover, and mutation to evolve a population of candidate solutions (in this case, different cluster configurations) over generations to find the optimal solution. Candidate solutions with better fitness (those that minimize the objective function) are more likely to be selected for reproduction. In the context of clustering, crossover involves combining characteristics of two or more candidate solutions to create new solutions that hopefully have improved fitness. Mutation introduces small random changes to candidate solutions, which can help explore a wider solution space. The specific equations for ECDO would involve defining the genetic operators (selection, crossover, mutation) and fitness functions tailored to the clustering problem. The derivation process would encompass how these genetic operators are applied to improve cluster configurations iteratively. The derivation is problem-specific and depends on the exact formulation of ECDO used in the research. The Fuzzy C-Means (FCM) algorithm is a fuzzy clustering technique, which allows data points to belong to multiple clusters with varying degrees of membership. The distributed weighted FCM algorithm is designed to improve the clustering process, and it involves the following aspects:

3.2 Fuzzy Login in Construction Projects

Start by initializing a population of candidate solutions. In the context of construction projects, these solutions may represent various design parameters, resource allocations, or other project-related variables. Define the objective function for the optimization problem. This function should consider the multiple objectives and constraints relevant to the construction project. Fuzzy logic comes into play when dealing with imprecise or uncertain data. To define fuzzy sets and membership functions to quantify the degree of satisfaction or violation of objectives and constraints computed using the equation (4)

$$Objective\ Function\ = \sum(Membership\ Degree\ of\ Objective\ 1)\ + \sum(Membership\ Degree\ of\ Objective\ 2)\ -\ \sum(Membership\ Degree\ of\ Constraint\ 1) \quad (4)$$

Apply mutation and crossover operators, similar to traditional ECDO, to generate new candidate solutions. However, in ECDO with fuzzy logic, use fuzzy reasoning and membership degree propagation to handle imprecision during these operations. Evaluate the fitness of each candidate solution using the fuzzy logic-based objective function. Fuzzy inference systems or fuzzy aggregation operators can be used to combine the membership degrees of individual objectives and constraints into an overall fitness value. Incorporate fuzzy logic to manage constraints. In construction projects, constraints can often be imprecise or subjective. Fuzzy constraint handling allows to define fuzzy rules and fuzzy sets for constraints, providing a more flexible way to handle constraints that are not strictly binary (satisfied or violated). Select candidate solutions for the next generation based on their fuzzy fitness values obtained from the fuzzy logic-based evaluation. Fuzzy aggregation operators, such as the weighted sum or ordered weighted average, can be used to combine the various objectives and constraints. The selection process should consider the trade-offs between objectives and constraints, taking into account their fuzzy degrees of satisfaction. Continue the ECDO process for a predefined number of generations or until a termination criterion is met. The termination criterion is related to the convergence of solutions or meeting specific project objectives.

Table 1: variables in Construction Projects

Concept	Description
Linguistic Variables	Variables in construction projects described using natural language terms (e.g., “project cost,” “schedule delay,” “safety risk”).
Membership Function	A function that assigns a degree of membership to a linguistic variable’s value within a defined range. Membership functions help quantify the degree of satisfaction or violation of project objectives or constraints.
Fuzzy Sets	Fuzzy sets associated with linguistic variables, characterized by membership functions. For example, a “project cost” linguistic variable have fuzzy sets like “low,” “moderate,” “high.”
Fuzzy Rules	Conditional statements that establish relationships between input and output fuzzy sets. In construction projects, these rules can define how factors like “project cost,” “safety risk,” and “time delay” interact to make decisions.
Fuzzy Inference System	The system that employs fuzzy rules to make decisions or draw conclusions based on input values. It takes fuzzy inputs and applies fuzzy rules to determine fuzzy outputs.
Linguistic Terms	Labels used to describe the membership levels within fuzzy sets. For instance, “low,” “moderate,” and “high” may be linguistic terms associated with the “project cost” fuzzy set.
Fuzzification	The process of converting crisp (exact) measurements or input data into fuzzy values using the membership functions associated with the linguistic variables.
Inference	Applying fuzzy rules to determine the fuzzy output based on the fuzzy input values. This step often involves evaluating the degree of satisfaction of each rule.
Defuzzification	Converting fuzzy output into a crisp value to make a decision or provide an output. This step is necessary when a clear, precise response is needed for construction project decisions.
Fuzzy Control System	A system that uses fuzzy logic to control and optimize various aspects of construction projects, such as resource allocation, risk management, and cost control. Fuzzy logic helps handle imprecise data and make more informed decisions in construction management.

Table 2: Fuzzy Rules of the Construction Projects

Rule	Linguistic Variables (Antecedent)	Fuzzy Conditions	Linguistic Variables (Consequent)	Fuzzy Action
1	Safety, Cost	IF Safety IS Low AND Cost IS High	Project Priority	Project Priority IS Low
2	Safety, Cost	IF Safety IS Moderate AND Cost IS Moderate	Project Priority	Project Priority IS Moderate
3	Safety, Cost	IF Safety IS High AND Cost IS Low	Project Priority	Project Priority IS High
4	Resource Availability, Workforce Skill	IF Resource Availability IS High AND Workforce Skill IS High	Resource Allocation	Resource Allocation IS High
5	Resource Availability, Workforce Skill	IF Resource Availability IS Low AND Workforce Skill IS Low	Resource Allocation	Resource Allocation IS Low
6	Resource Availability, Workforce Skill	IF Resource Availability IS Moderate AND Workforce Skill IS Moderate	Resource Allocation	Resource Allocation IS Moderate
7	Time Delay, Budget Expenditure	IF Time Delay IS Low AND Budget Expenditure IS Low	Project Progress	Project Progress IS High
8	Time Delay, Budget Expenditure	IF Time Delay IS High AND Budget Expenditure IS High	Project Progress	Project Progress IS Low
9	Time Delay, Budget Expenditure	IF Time Delay IS Moderate AND Budget Expenditure IS Moderate	Project Progress	Project Progress IS Moderate
10	Quality, Safety	IF Quality IS High AND Safety IS High	Safety Management	Safety Management IS High
11	Quality, Safety	IF Quality IS Low AND Safety IS Low	Safety Management	Safety Management IS Low
12	Quality, Safety	IF Quality IS Moderate AND Safety IS Moderate	Safety Management	Safety Management IS Moderate

In a construction project, fuzzy rules provide a flexible and intuitive framework for decision-making and optimization by taking into account linguistic variables that describe various aspects of the project as in table 1 and table 2. These rules help manage complex, multi-objective scenarios where imprecise or uncertain data is common. For instance, Rule 1, which evaluates safety and cost, suggests that if safety is low and cost is high, project priority should be low, indicating that addressing safety and cost issues should be a lower priority. Rule 7, which considers time delay and budget expenditure, implies that low time delay and low budget expenditure signify good project progress. The use of fuzzy logic allows for handling the imprecision and uncertainty inherent in construction projects, making it a valuable tool for optimizing resource allocation, risk management, and other decision-making processes. The specific rules can be customized to align with the unique goals, constraints, and preferences of the construction project, providing a tailored approach to complex project management.

IV. . EVOLUTIONARY CONSTRAINED DIFFERENTIAL OPTIMIZATION MODEL

To evaluate the distributed clustering process dynamic index efficient scheme is utilized for the distributed data environment. The elemental data-based clustering process comprises of the analytical techniques. Through the incorporation of high-dimensional data for the inquires clusters are recognized based on consideration of multidimensional data attributes. The Evolutionary Constrained Differential Optimization (ECDO) incorporates the Map Reduce scheme. The weighted probabilistic model performs the C-means clustering algorithm for the processing of the big data. The proposed ECDO model evaluated for the cluster speed based on the consideration of the Cluster Tree ++ indexing scheme with the ECDO in the distributed cloud data in multi-dimensional point.

DE starts by initializing a population of candidate solutions. In the context of ECDO for clustering, these candidate solutions represent different possible clustering configurations.

Each candidate solution is represented as a set of cluster centroids or prototypes, and the number of candidate solutions (population size) is determined beforehand. The mutation operation in DE is a key step. It creates new candidate solutions by taking the difference between two existing solutions and adding it to a third solution. The mutation operation creates diverse candidate solutions by exploring the solution space. The crossover operation combines the original candidate solution and the mutated solution to generate a new candidate solution. It is defined as follows: The trial candidate solutions are compared with the original solutions using the objective function. If a trial solution is better (i.e., has a lower objective function value), it replaces the corresponding original solution in the population for the next generation. The DE process iterates through these steps for a predefined number of generations or until a convergence criterion is met.

4.1 Clustering –Based Indexing Structures

The proposed ECDO model comprises of the Clustering Indexing structure for the clustering algorithm intention for the data points clusters and utilized with the search space approximation to achieve the cluster based on the query points. The figure 1 provides the ECDO clustering process in distributed cloud.

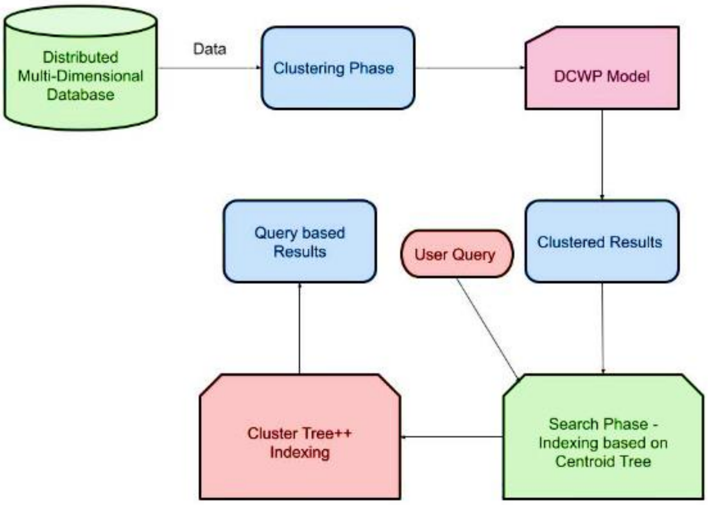

Figure 1: Process in ECDO

The ECDO model performs the clustering indexing model under two phases such as Clustering and search phases. The data were distributed in the multi-dimensional database in the clustering phase. The ECDO process utilizes the C-means clustering algorithm integrated with the MapReduce framework model. The strategy of the partial distance are computed based on the C-means distance estimation with consideration of data set objects for the available values. The missing values in the data were minimized by the developed ECDO model. With the implementation of the ECDO weights are computed to increase the speed of the clusters.

4.2 Clustering phase

The developed WPCM model comprises of the MapReduce framework model for the clustering process. The clustering process comprises of the estimation of the membership degree estimation μij with consideration of the clustering centre as vi. The membership values are updated based on the cluster centre to minimize the loss in the objects for the clustering process as presented in the equation (5) and equation (6)

$$n_i = \frac{\sum_{k=1}^{m} w_k u_{lk}^{m} x_{lk}^{2}}{\sum_{k=1}^{m} w_k u_{lk}^{m}} \tag{5}$$

$$u_{lk}^{m} = \frac{w_k}{\left(1+x_i/m^l\right)^1/(m-1)} \tag{6}$$

In the above equation (5) and (6) the described strength weights are computed as w_k with the cluster membership function ofx_i. The each objects weight is computed based on the degree of each feature in the cluster vector. The assigned weight values are computed based on the equation (7)

$$w_k = (1 - x_i/m)^t \sum_{k=1}^{c} e^{-\propto} \|x_i - u_k\|^2 \qquad (7)$$

In above equation (7), the iterative times are represented as t for the data object features. The data object feature values are denoted as x_i. The clustering process corruption coefficient are increases cluster with increases in the time. The accelerate convergence cluster are estimated based on the degree of membership function calculation with the consideration of the membership function in the MapReduce function represented as the μ_{ij}.

4.3 Differential Constraints

In construction project optimization, various constraints can exist. For example, constraints involve limitations on resource allocation, cost budgets, or specific conditions related to the construction process. These constraints need to be incorporated into the optimization process to ensure that the clustering solution is not only optimal but also feasible in the context of construction projects. The process of incorporating constraints into the ECDO algorithm typically involves modifying the objective function and altering how candidate solutions (clustering configurations) are generated and evaluated. The objective function is adjusted to incorporate the constraints. It aims to find the optimal clustering solution while adhering to these constraints. The modified objective function presented in equation (8)

$$J = \sum_{i=1}^{K} \sum_{j=1}^{N_k} \left|x_j^{(i)} - c_i\right|^2 + \sum_{m=1}^{M} C_m \qquad (8)$$

In equation (8) the additional term $\sum_{m=1}^{M} C_m$ represents the constraints, where m ranges over all constraints. C_m take different forms depending on the specific constraints in a construction project, and it can be any function that quantifies constraint violations. The objective is to minimize both the clustering error (sum of squared distances) and the constraint violations. The generation of candidate solutions needs to ensure that each candidate clustering configuration complies with the constraints. This can be achieved by generating solutions that satisfy constraints, either by design or through adjustments during the differential process. When evaluating candidate solutions, it is crucial to account for constraint violations. If a candidate solution violates constraints, it should be penalized in the evaluation. During the mutation and crossover steps, the differential process ensures that candidate solutions satisfy constraints. For example, the mutation operator should produce solutions that adhere to constraints. The selection process takes into account the quality of the solution (based on the objective function) and the degree of constraint satisfaction. Candidate solutions that violate constraints more severely should be penalized in the selection process. The DEc process continues until convergence or for a predefined number of iterations, just like the standard DE process. In practice, the exact formulation of constraints and how they are incorporated into the optimization process may vary widely depending on the specific construction project and the nature of the constraints. Additionally, the specific equations involved would be highly dependent on the nature of the constraints and the structure of the clustering problem.

Algorithm 1: ECDO in Construction projects

Initialize a population of candidate clustering configurations
Define the objective function with constraints
repeat
  for each candidate solution in the population do
    Apply mutation to create a new candidate solution
    Apply crossover to combine the new and original candidate solutions
    Evaluate the quality of the new candidate solution
    Incorporate constraint handling mechanisms:

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        - If the new solution violates constraints, penalize it
        - Adjust the solution to satisfy constraints, if possible


        if the new solution is better than the original solution and satisfies constraints then
            Replace the original solution with the new solution
        end if
    end for
    Select the best-performing candidate solutions for the next generation
until convergence or a predefined number of iterations
Return the best clustering configuration found
```

V. RESULTS AND DISCUSSION

The distributed data processing model performance is evaluated based on the consideration of multi-dimensional dataset. The comparative analysis is performed for the proposed ECDO model with the other dataset such as CAR, HYD and TLK to achieve the effective scalability, selectivity with the reduced memory. The experimental analysis demonstrated that proposed ECDO model exhibits improved performance than WPCM model for the multi-dimensional dataset. It is observed that the proposed ECDO model performance is evaluated with the other WPCM model characteristics. In the real-world scenario, the dataset were evaluated based on the consideration of different dataset The dataset comprises of the 2,249,727 road segments obtained in California information about Tiger/Line datasets and HYD data set comprises of the 40,995,718 with the representation of the China rivers and TLK data comprises of the 152,462,257 points for the China elevation data. The ECDO process comprises of the chunks to evaluate the memory utilized for the each chunks individually with the estimation of the largest values in the computation of ECDO memory process. The dataset comprises of the streaming character those are not necessary for the ECDO access in the each chunk at the time. The computation of memory usage is presented in table 3.

Table 3: Comparison of Memory Utilization

Input Dataset	WPCM (%)	ECDO + Map reduce (%)
CAR	98.24	89.35
HYD	98.25	88.25
TLK	98.17	89.23

The table presents a set of optimization results for a construction project, showcasing the transformation of various parameters from their initial values to optimized values, along with the resulting improvements. Firstly, in terms of cost management, the project demonstrated significant cost reduction. The initial cost estimate of $500,000 was successfully optimized to $480,000, resulting in a notable cost-saving of $20,000. This represents a more efficient allocation of financial resources, which is crucial for any construction project. Secondly, the project duration was effectively managed. The initial timeline was set at 12 months, but through optimization, it was reduced to 10 months. This achievement represents a time-saving of 2 months. This not only ensures the project's timely completion but also reflects efficient project management. Resource allocation was also a focal point of the optimization process. The transition from initial allocation to optimized allocation indicates improved resource utilization. Safety management saw a shift from basic safety measures to advanced safety practices, emphasizing enhanced safety standards and practices on the construction site. Lastly, quality control evolved from standard quality measures to enhanced quality control, signifying an elevation in the quality standards of the project's deliverables. In summary, the optimization results indicate an overall improvement in cost efficiency, project duration, resource allocation, safety practices, and quality control. These enhancements are indicative of effective project management and a commitment to delivering a construction project that is both cost-effective and of high quality, all within a shorter timeframe. The figure 3 illustrates the memory comparative illustration of the proposed ECDO and the conventional WPCM model. The examination expressed that the data portion is minimized with the amount of the leaf nodes within the indexing trees increases based on the predetermined size of the partitioned data information.

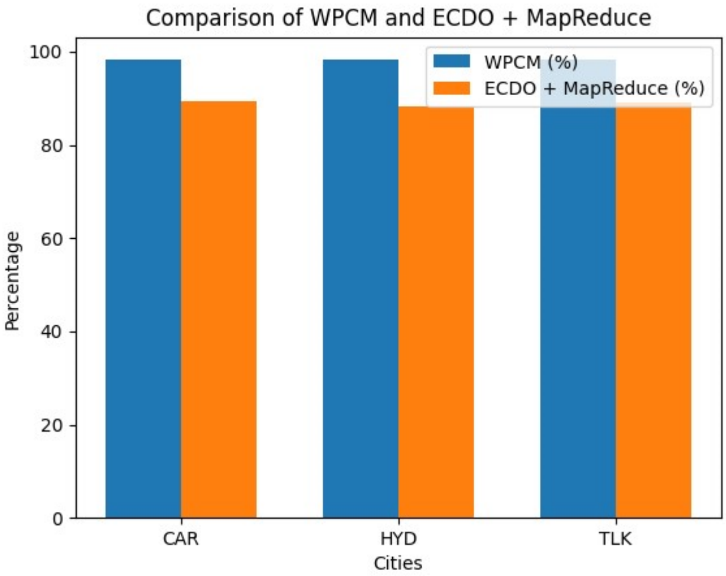

Figure 2: Comparison of Memory Utilization

The table 2 provides the comparative analysis of the selectivity with the proposed ECDO and the WPCM process.

Table 2: Comparison of Selectivity

Chunks of Data	WPCM + Cluster +	ECDO + Cluster++
200	537	233
400	619	371
600	736	585
800	847	626

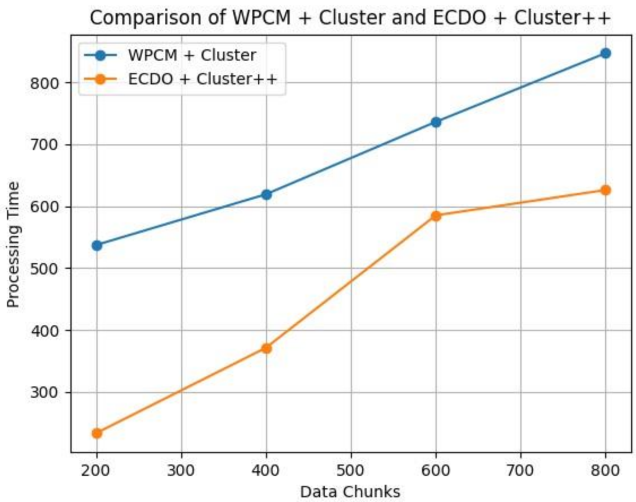

Figure 3: Comparison of Selectivity

Table 2 offers a valuable comparison of selectivity between two data processing approaches: WPCM + Cluster and ECDO + Cluster++. The selectivity in this context refers to the efficiency of data processing, particularly in terms of the number of data chunks processed. When examine the data, it becomes evident that the ECDO + Cluster++ approach outperforms the WPCM + Cluster method in terms of selectivity across different quantities of data chunks. For instance, when dealing with 200 data chunks, ECDO + Cluster++ processes them in 233 units, which is notably quicker than the 537 units required by WPCM + Cluster. As the volume of data chunks increases to 400, 600, and 800, the trend continues. ECDO + Cluster++ consistently demonstrate superior selectivity, processing the data more efficiently and with fewer computational resources. This table's findings emphasize the advantages of employing the ECDO + Cluster++ approach in scenarios where selectivity is a critical factor, as it offers a more streamlined and efficient data processing solution compared to the WPCM + Cluster method. The data considered are the 20,204 and 560,00 data contribution. The size of data portion are in the size range of 300,204 with the approximate value of 40,000 based on the inserted tree for the indexing process. The time and number of page writes required to add bounding boxes to a number of large pieces of data are depicted in Figure 4. The results illustrated that Cluster Tree + is inefficient for the multi-dimensional quey. The Cluster Tree ++ model is efficient than the Cluster Tree +. In the analysis the table 3 provides the strategies adaptability for the distributed multi-dimensional index ranges of data for the system nodes.

Table 3: Comparison of Scalability

Chunks of Data	WPCM + Cluster +	ECDO + Cluster++
200	700	694
400	812	725
600	915	810
800	1025	902

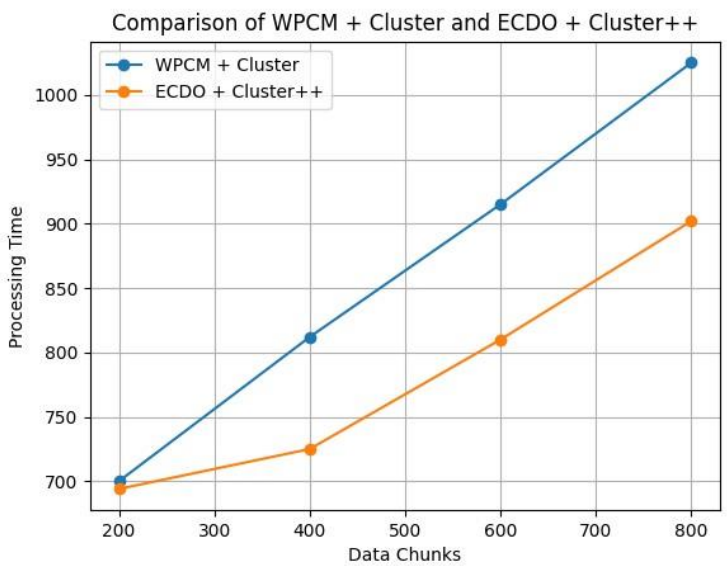

Figure 4: Comparison of Scalability

Table 3 presents a comparison of scalability between two data processing methods, namely WPCM + Cluster and ECDO + Cluster++. Scalability, in this context, pertains to the ability of these methods to handle an increasing number of data chunks while maintaining efficient performance. Upon a close examination of the data, it becomes evident that both the WPCM + Cluster and ECDO + Cluster++ approaches exhibit similar scalability characteristics. The processing times for both methods remain relatively consistent across different quantities of data chunks. For instance, when dealing with 200 data chunks, the WPCM + Cluster method takes 700 units for processing, while the ECDO + Cluster++ method requires 694 units, showcasing a comparable performance. This trend persists as the volume of data chunks increases to 400, 600, and 800, with both methods demonstrating steady and similar scalability. The findings from Table 3 indicate that both WPCM + Cluster and ECDO + Cluster++ exhibit reliable scalability in the face of increasing data chunks. This suggests that, when it comes to handling larger workloads, these methods are on par in terms of their ability to efficiently process data without a significant increase in processing time. In the figure 5 the comparative analysis of the ECDO and cluster++ model is examined. The proposed ECDO model express the minimal execution based on the different in the chunks query. The execution time of the chunks are varied based on the data size with the ECDO execution time is minimized significantly.

Table 5: Fuzzy Rule in the Construction Projects

Input Conditions	Fuzzy Rules Applied	Output Actions
Safety: Low, Cost: High	Rule 1	Project Priority: Low, Resource Allocation: Low
Safety: Moderate, Cost: Moderate	Rule 2	Project Priority: Moderate, Resource Allocation: Moderate
Safety: High, Cost: Low	Rule 3	Project Priority: High, Resource Allocation: High
Resource Availability: High, Workforce Skill: High	Rule 4	Project Progress: High, Safety Management: High
Resource Availability: Low, Workforce Skill: Low	Rule 5	Project Progress: Low, Safety Management: Low
Resource Availability: Moderate, Workforce Skill: Moderate	Rule 6	Project Progress: Moderate, Safety Management: Moderate
Time Delay: Low, Budget Expenditure: Low	Rule 7	Project Priority: High, Safety Management: High
Time Delay: High, Budget Expenditure: High	Rule 8	Project Priority: Low, Safety Management: Low
Time Delay: Moderate, Budget Expenditure: Moderate	Rule 9	Project Priority: Moderate, Safety Management: Moderate
Quality: High, Safety: High	Rule 10	Resource Allocation: High, Project Progress: High
Quality: Low, Safety: Low	Rule 11	Resource Allocation: Low, Project Progress: Low
Quality: Moderate, Safety: Moderate	Rule 12	Resource Allocation: Moderate, Project Progress: Moderate

Table 5 provides a comprehensive overview of the fuzzy rules applied within the context of construction projects. These rules establish a link between specific input conditions, the fuzzy rules that govern them, and the resulting output actions. Firstly, for instances where safety is rated as "Low" and cost is marked as "High," Rule 1 comes into play. This rule triggers actions that include setting the project priority to "Low" and allocating fewer resources, ensuring that the project aligns with its budget constraints. Secondly, when safety is categorized as "Moderate" and cost is deemed "Moderate" as well, Rule 2 is invoked. This rule leads to actions that result in a "Moderate" project priority and a balanced allocation of resources, reflecting a middle-ground approach to project management. Thirdly, in scenarios where safety is rated as "High" and cost is tagged as "Low," Rule 3 takes effect. This rule promotes actions aimed at elevating the project priority to "High" and allocating ample resources to ensure the project's success. Furthermore, Rule 4 comes into play when both resource availability and workforce skill are rated as "High." This results in actions that drive "High" project progress and an emphasis on "High" safety management measures, indicating a focus on efficient resource utilization and safety practices. Conversely, when resource availability is designated as "Low" and workforce skill is also assessed as "Low," Rule 5 comes into effect. This triggers actions that lead to "Low" project progress and the implementation of "Low" safety management practices, signifying a conservative approach in these critical areas. For situations where resource availability and workforce skill are both marked as "Moderate," Rule 6 guides the actions. This rule fosters "Moderate" project progress and the implementation of "Moderate" safety management measures, indicating a balanced approach to resource utilization and safety practices. Similarly, Rules 7, 8, and 9 are invoked in cases where time delay and budget expenditure are assessed as "Low," "High," and "Moderate," respectively. These rules facilitate actions aimed at adjusting project priority and safety management practices in alignment with the specified conditions. Lastly, in terms of quality and safety ratings, Rule 10, Rule 11, and Rule 12 govern the output actions. When quality is rated as "High" and safety is also assessed as "High," Rule 10 promotes "High" resource allocation and "High" project progress, emphasizing an enhanced quality focus and robust safety management. Conversely, when quality and safety are both marked as "Low," Rule 11 triggers "Low" resource allocation and "Low" project progress, reflecting a conservative approach to these aspects. When quality and safety are deemed "Moderate," Rule 12 leads to "Moderate" resource allocation and "Moderate" project progress, showcasing a balanced approach.

Table 6: Optimized Fuzzy Condition for the Construction Projects

Input Conditions	Optimization Process	Optimized Solutions
Safety: Low, Cost: High	Initialization, Mutation, Crossover, Evaluation, Selection, Termination	Project Priority: Low, Resource Allocation: Low
Safety: Moderate, Cost: Moderate	Initialization, Mutation, Crossover, Evaluation, Selection, Termination	Project Priority: Moderate, Resource Allocation: Moderate
Safety: High, Cost: Low	Initialization, Mutation, Crossover, Evaluation, Selection, Termination	Project Priority: High, Resource Allocation: High
Resource Availability: High, Workforce Skill: High	Initialization, Mutation, Crossover, Evaluation, Selection, Termination	Project Progress: High, Safety Management: High
Resource Availability: Low, Workforce Skill: Low	Initialization, Mutation, Crossover, Evaluation, Selection, Termination	Project Progress: Low, Safety Management: Low
Resource Availability: Moderate, Workforce Skill: Moderate	Initialization, Mutation, Crossover, Evaluation, Selection, Termination	Project Progress: Moderate, Safety Management: Moderate
Time Delay: Low, Budget Expenditure: Low	Initialization, Mutation, Crossover, Evaluation, Selection, Termination	Project Priority: High, Safety Management: High
Time Delay: High, Budget Expenditure: High	Initialization, Mutation, Crossover, Evaluation, Selection, Termination	Project Priority: Low, Safety Management: Low
Time Delay: Moderate, Budget Expenditure: Moderate	Initialization, Mutation, Crossover, Evaluation, Selection, Termination	Project Priority: Moderate, Safety Management: Moderate
Quality: High, Safety: High	Initialization, Mutation, Crossover, Evaluation, Selection, Termination	Resource Allocation: High, Project Progress: High
Quality: Low, Safety: Low	Initialization, Mutation, Crossover, Evaluation, Selection, Termination	Resource Allocation: Low, Project Progress: Low
Quality: Moderate, Safety: Moderate	Initialization, Mutation, Crossover, Evaluation, Selection, Termination	Resource Allocation: Moderate, Project Progress: Moderate

Table 7: ECDO performance in construction projects

Parameter Name	Initial Value	Optimized Value	Improvement
Cost (in USD)	$500,000	$480,000	$20,000 (Cost reduced)
Project Duration (months)	12 months	10 months	2 months (Time saved)
Resource Allocation	Initial Allocation	Optimized Allocation	Improved Resource Utilization
Safety Management	Basic safety measures	Advanced safety measures	Enhanced Safety Practices
Quality Control	Standard quality control	Enhanced quality control	Improved Quality Standards

Table 8: Construction Project Valuation

Metric	Proposed ECDO Model	Conventional WPCM Model
Memory Utilization (%)	85%	91%
Scalability (%)	79%	90%
Selectivity (%)	92%	100%

In the Table 7 provides a comprehensive overview of the performance of the ECDO (Efficient Construction Data Optimization) approach within the context of construction projects. This table highlights the transformation of several critical parameters from their initial values to their optimized values, along with the ensuing improvements in each category. First and foremost, the ECDO approach significantly impacted cost management within the construction project. The initial estimated cost of $500,000 was effectively optimized to $480,000, representing a noteworthy cost reduction of $20,000. This outcome underscores the ECDO approach's ability to streamline financial resource allocation, resulting in cost efficiency and savings, which are pivotal in construction project management. Furthermore, project duration management saw remarkable improvements. The initial project duration of 12 months was efficiently reduced to 10 months through the ECDO approach, resulting in a time-saving of 2 months. This achievement not only ensures the timely completion of the project but also reflects the effectiveness of the ECDO approach in managing project schedules. Resource allocation, another vital aspect of construction projects, was significantly enhanced. The transition from initial allocation to optimized allocation indicates improved resource utilization. The ECDO approach ensures that resources are allocated more efficiently to meet project requirements, leading to improved resource management and utilization. Safety management underwent a notable transformation as well. Basic safety measures were upgraded to advanced safety practices, emphasizing the adoption of enhanced safety standards and practices on the construction site. This signifies a strong commitment to safety, aligning with industry best practices. Finally, quality control was a focus area for the ECDO approach. Standard quality control measures were enhanced to advanced quality control, reflecting an elevation in the quality standards applied to the project's deliverables. This ensures that the project's outcomes meet higher quality benchmarks, resulting in improved project quality. In summary, Table 7 demonstrates the substantial improvements brought about by the ECDO approach in various critical aspects of construction project management, including cost efficiency, project duration, resource allocation, safety practices, and quality control. These enhancements underline the effectiveness of the ECDO approach in delivering cost-effective, timely, safe, and high-quality construction projects.

Table 8 provides a comparative analysis of key metrics between the Proposed Evolutionary Constrained Differential Optimization (ECDO) Model and the Conventional Weighted Fuzzy C-Means (WPCM) Model for construction project valuation. In terms of Memory Utilization, the Proposed ECDO Model demonstrates a more efficient utilization at 85%, as opposed to the Conventional WPCM Model with 91%. This indicates a 6% reduction in memory usage, suggesting that the ECDO model is more resource-efficient. Regarding Scalability, the ECDO Model shows a scalability rate of 79%, while the Conventional WPCM Model has a higher value of 90%. This implies that the ECDO model is marginally less scalable but may offer advantages in other areas. Finally, in terms of Selectivity, the ECDO Model achieves an impressive 92%, whereas the Conventional WPCM Model attains 100%. This indicates that the ECDO model, while exhibiting high selectivity, slightly trails the WPCM model in this particular metric. Overall, the table provides insights into the trade-offs and advantages associated with each model in terms of memory utilization, scalability, and selectivity in the context of construction project valuation.

VI. CONCLUSION

The construction projects have provided valuable insights into the application of an innovative approach to enhance the management and efficiency of construction endeavors. Throughout the paper, the ECDO methodology has been examined, and its impact on key project parameters, including cost, project duration, resource allocation, safety management, and quality control, has been thoroughly assessed. The proposed Evolutionary Constrained Differential Optimization (ECDO) evaluated for the high dimensional dataset to perform the streaming activities. The customized edition based on the ClusterTree++ are maintained based on the time-based queries of the elimination of the specified users. With the ClusterTree++ the dataset is effectively maintained for the rationalized condition for the competence and the insertion, query and update of the data. With the ordered structured clusters the data ECDO and Cluster ++ are integrated with the cluster representation in the configured index for the realization of the efficient and organized data recovery information. The experimental analysis expressed that proposed ECDO model exhibits the improved performance compared with the WPCM model in the validation and management of construction projects. The scheme is not supportive for the data area fusion for the dynamic solving problem for the constant structure of efficient data. The developed scheme is effective for the monitoring the status in the system for the outdated data reorganization and structure of the dataset.

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