Q23	Responded to questions
Q24	Better evaluation to measure course objectives
Q26	Treated all students equally

Table 3 Parameter Settings

Parameters	Value
No. of agents (a)	50
Max. no. of iterations (t)	100
No. of instructors (C)	3
No. of attributes (d)	14

Then, Search Direction Sea_D = (Sea_{D1}, Sea_{D2} ……. Sea_{Dk}) and the heuristic search action Sea_A = (Sea_{A1}, Sea_{A2}… Sea_{A3}). In Table4 the search direction determines the centroid of the LO at the i^{th} agent with dimension d. The dimension d denotes the dimensionality of the test data records. Initially, the Sea_Dset to 1 and sequentially updates during the search progression. Toward the finish of the ebb and flow cycle, another centroid is produced utilizing the momentum centroid, ebb and flow look course and ebb and flow seek step. Some change is perceptible in the first and second highlights, though the third and fourth highlights stay unaltered. Therefore, at the next iteration, for both features 1 and 2, the search process continues on the current direction. For the 3rd feature, the current search direction is 0, which means in the previous iterations no improvement happened to this feature in both directions**.** Thus, for the following emphasis, the hunt step is partitioned by 2 and the pursuit bearing is set to 1. In the respect of the last component, the inquiry heading is set to - 1 with a specific end goal to scan for a superior arrangement the other way since there is no opportunity to get better in the present course**.**

Table 4. Heuristic Information about Agents in the Teaching Routes

	Q5	Q11	Q13	Q19
Centroid $_{Pres}$	4.53	1.24	7.56	0.32
Sea_D	1	-1	0	1
Sea_A	0.2	0.3	0.1	0.09
Centroid $_{nvalue}$	4.82	1.19	7.36	0.44
Centroid $_{fvalue}$	4.82	1.19	7.36	0.36

In the education management scenario, the heterogeneity of the data in various learning management systems describes a lot of issues in data sharing and prediction. The issues like impeccable data integration, retrieving accurate result for user queries and discovering the informed search are under heterogeneous teaching systems. Though, several e-learning architectures are introduced, the selection and recommendation of the best web service are not widely explored. Teaching efficacy was based on the foundation of self-efficacy. The social learning theory and made it a definite of the conviction that one can successfully execute the behavior required to produce the outcomes. This concept more narrowly defined teacher confidence is less influenced by emotional factors outside the realm of teaching than teacher self-efficacy. Ant colony optimization algorithms has applied for the combinatorial optimization of instructor evaluation, which is dynamic problems in nature due to the real variables, stochastic problems, multi-targets and parallel implementations due to the subject taught and level of students understanding. ACO produce near-optimal solutions for Predicting Instructors Performance in Higher Education Systems Using ACO Systems, the results will be changing dynamically; the Ant Colony algorithm can be run continuously and adapt to changes in real time [RA-2].

5. Conclusion

Ant colony optimization algorithm is a delicate processing technique that demonstrates a handles vulnerability and deficiency of an issue and builds the way that has most extreme adjustment. This investigation proposes a calculation in view of the insect settlement improvement strategy and the possibility of idea guide to consequently build the appropriate instructing way that can adjust to the students. In this paper, we suggest a novel ant colony optimization model which assists both students and instructors [RA-3]. The framework executes in two steps, i) to place the teaching objects in its appropriate and accurate position using Ant as an intelligent agent. ii) Suggesting the knowledge for predicting the instructor's performance in a collaborative environment. Experimental analysis has been carried out in Turkiye Student Dataset in which 14 attributes are selected. Since the aim of the study is to predict and suggest the teaching style of the instructors using student feedback data. Information filtering agent is used to find the appropriate teaching objects for giving instructors. With the help of filtered information, a certain set of teaching styles was predicted from the initialized teaching objects. From the results, the significant attributes are Q5, Q11, Q13 and Q19 play a vital role in suggesting and predicting the instructor's performance. On comparison with existing models, Inherent parallelism of ACO performs better than other Optimization algorithms such as particle swarm optimization (PSO), cuckoo search optimization (CSO) for predicting instructor performance. Positive Feedback of ACO leads for rapid discovery of good prediction with more accuracy. ACO provides crisps results and PSO is applicable for problems, which are in fuzzy nature[RA-3].

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