How to Cite:
Arvindhan, M., & Dhanaraj, R. K. (2022). The firefly technique with courtship training optimized for load balancing independent parallel computer task scheduling in cloud computing. *International Journal of Health Sciences*, *6*(S1), 8740–8751. https://doi.org/10.53730/ijhs.v6nS1.6999

The firefly technique with courtship training optimized for load balancing independent parallel computer task scheduling in cloud computing

M. Arvindhan
Research Scholar, Galgotias University
Email: m.arvindhan@galgotiasuniversity.edu.in

Dr. Rajesh Kumar Dhanaraj
School of Computing Science and Engineering, Galgotias University,
Email: sangeraje@gmail.com

***Abstract*---**Load Balancing strategies is essential provisioning towards cloud environments is a hard challenge due of the situation dynamic nature and varying additional actions selves. Load balancing approaches are spoken at a data center levels in just this investigation. A much more effective source management technique for virtualizing data centers that raises the quantity of computers to satisfy the necessities of changing assignments requiring relocation is suggested in this study. The anticipated method, termed First-ahead load balancing VM Allocation (FALB), incorporates the optimization unbiased, which constructs a accurate formula of UPMSP with sequential setup weeks back basic feasible. In particular, an enhanced firefly algorithm along with engagement learning is planned. Ultimately, in order to offer numerical solutions inside an appropriate timescale, the suggested algorithm is utilized to calculate the UPMSP with set of images process time. FALB is contrasted the with best solution availability of Cloud centered on VM migration dubbed Local Regression-Minimum Migration Time (LR-MMT) (LR-MMT).

***Keywords*---**Load Balancing, Auto scaling, Cloud Computing, FALB LB, VM Allocation.

Introduction

Cloud computing obligates developed a significant standard of computers and IT service delivery. Nonetheless, for just about any probable consumer of cloud computing, consumers determination ask "can I belief this cloud service?"

Additionally, whatever precisely does "trust" entail in the framework of the internet? Whatever is the source of that trust? Uncertainty the qualities of a cloud service (or for a service provider) have been usage as confirmation for faith judgement on a service (or provider correspondingly), about what foundation would consumers consider the characteristics asserted by cloud services? As make a speech in (Ewees et al., 2021) , "the expanding relevance of cloud computing varieties it progressively necessary that we struggle through the concept of trust inside the cloud and also in what way the consumer, provider, society at large develop that trust." Service providers give consumers sorts of services, based on the customer interest three major services are Platform as a Service (PaaS), Software as a Service (SaaS), and Infrastructure as a Service (IaaS), over data centers. As consumers' desires aimed at the services given by data centers expand, the quantity of vitality required by data centers growths linearly. Upsurges of 48 percent and 34 percent are anticipated for overall world energy depletion and CO_2 emissions, correspondingly, concerning 2020 and 2040. In furthermore, minimizing the cost for services and raising the profitability are further objectives of suppliers. For this reasons, while attempting to reduce electricity cost, the effectiveness of the service supplied to consumers must also be addressed(Huang et al., 2022).

Since the beginning of this year, the study on UPMSP and its derivative products has received a significant amount of attention. The goal of optimization in UPMSP is frequently to reduce the total completion time to the bare minimum. The simultaneous timetabling of a UPMSP, which necessarily involves the use of two or more processes, poses a significant challenge to the peace treaty in many instances. The UPMSP, whose procedure durations are subject to classification, operates in a non-deterministic polynomial surroundings, making it difficult to understand and explain. Cutting planes algorithms, the branch - and - bound algorithm, and other nearly exact technologies have been proposed to resolve UPMSPs whenever the set - up occasions are ignored, such as the having to cut planes algorithm and the branch - and - bound algorithm, among others (*Changyuan L, Yuyan R, Xiaojun B (2020) Timing Optimizati... - Google Scholar*, n.d.). Although precise algorithms are efficient, they are not as well suited for strong scenarios because of their inefficient characteristics. Afterwards, in high-dimensional situations, theoretical algorithms are much more intentional in their application because they are more capable of identifying effective responses in a more timely and consistent manner in the cloud environment. In specific, Firefly Algorithm with Courtship Learning (FACL) is a variant of the Firefly Algorithm (FA), which is capable of performing well in unending goal optimization algorithms involving a large number of situations with a complexity. Because of the use of negligible hyperparameters as well as the simplicity of the building projects, this methodology is advantageous. Consequently, we aim to relate the FACL to resolve the UPMSP through sequence - dependent setup setup periods. Conversely, the male and female fascination factors employed by FACL diminish promptly throughout search phase, that varieties it easy the stop the examine prematurely and drop into to the optimal solution problem. With providing extra parameters, the exploration effectiveness of male firefly in courtship learning stage is boosted, so that for a program could mark the full usage of online connections of populace. Consequently, the facility of something like the system to break out into local optimum is boosted, and the global search routine is enhanced. Also available were a plethora of simulation studies that assessed the effectiveness of IFACL in trying to explain UPMSP by a set of images setup times, in addition to the previously mentioned studies. As a result of this effort, the following residual components have been assembled. The "Related work" section expands the scope of the related work(Wang et al., 2016). The detailed model of the UPMSP is described in greater detail in the portion "Mathematical modelling." The ahead of the upcoming "UPMSP constructed on firefly algorithm incorporating courtship learning" describe and understand the IFACL feature that has been proposed as an alternative to UPMSP. A demonstration of the unconventional discussion of the results are provided in the section titled "Simulation experiment." Finally, the "Conclusion" section contains a summary of the entire paper (Kim et al., n.d.).

.

Materials and Methods

Contemporary study on UPMSPs In the past couple of centuries, considerable development had been prepared in overcoming this tough challenge. Several precise search algorithms has been practical to UPMSP through sequence-reliant setup setup times. The model described through is the foundation of numerous Mixed Integer Linear Programming (MILP) methods, however optimality could only be definite in insignificant instances. Although precise methods has not been shown operative in real world instances of resolving this problem till recently, certain meta-heuristic algorithms had been proposed that answer the UPMSP through sequence-dependent process time (Jovanovic et al., n.d.). Another for an meta-heuristic techniques used to cope with a UPMSP per set of images make span is the Variable Neighborhood Search (VNS). Firstly, usage of VNS to answer high-dimensional UPMSP with set of images setup times, whichever aims to minimize completion time and weighting delay. And they likewise examined the guidance for classification dependent setup time among machines and workloads. Introduced a hybrid meta-heuristic approach that incorporates Simulated Annealing (SA), Ant Colony Optimization (ACO), and VNS algorithms to resolve the UPMSP which also reflects various set of images setup times, so has to minimize the time of tasks. ACO is also alternative meta heuristic method that effectively employed to UPMSP through set of images designated times. Offered an updated ACO algorithm for solving the UPMSP without sequential setup times in the instance of 20 machines and 240 tasks built an enhanced Salp Swarm Algorithm (SSA), and produced the emergent properties consequence for sequence-dependent UPMSP algorithm(Orts et al., 2020). Eventually realized the concurrent machine planning with modification time for example on an enhanced clone selection method, and has a improved performance as related through GA and the basic copy determine the desired (CSA) (Huang et al., 2020).

Firefly Algorithm standards

Firefly Approach is a modest and effective swarm intelligence algorithm for tackling difficult multi objective optimization problem in uninterrupted search process. The flashing and enticing behavior of fireflies is vital for their progression(Huang et al., 2020). A firefly by a intensity would attract a firefly by such a shadier illumination, and also the light output of the respectively firefly relies onto its intensity of light, such that, overall appropriateness of something like the optimization problem.

$$B_{p,q}(o_{p,q}) = \beta_0 \times e^{-\gamma r^2_{I,j}} \text{ ....(1)}$$

wherein o ,p,q is the Euclidian distance between two firefly xp and xq, and β0 denotes the initial attraction factor, whichever is normally described is Parameter γ has a fixed value into light absorption coefficient, whichever generally also 1. Considering 2 fireflies xp and xq particular at random in the very similar solution space, the distance r p,q among them is determined as follows:

$$r_{i,j} = \left\| x_i - x_j \right\| = \sqrt{\sum_{d=1}^{D} (x_{i,d} - x_{j,d})^2}. \qquad (2)$$

Where in D denotes the dimension for a problem, and d characterizes the d-th dimensionality for coordinates in a firefly. Other fireflies would travel into stronger firefly, then eventually the firefly individual would cluster everywhere the firefly using the utmost brightness to finish the optimization method(Peng et al., n.d.)

Modeling using mathematics Take a look at it again. In order to better understand the UPMSP by set of images setup periods, which would have been discussed and suggested and what would be premised on an altered firefly algorithm of trying to court knowledge, the following definitions are provided: – A scheduling problematic assumes that there were around N accessible jobs that need to be dispersed to M markedly different computers for finalization at time zero, and also that the mechanisms are autonomous to each other. – There'll be no implementation as a precautionary measure. – The scheduling embraces the assumption that there have been N obtainable jobs to be made available to M unassociated mechanisms for arithmetic at a time zero, and the computer systems are self-sufficient for one another. – The scheduling system embraces the assumption that there have been N accessible jobs to be made available to M unrelated processes for arithmetic at a time zero, and the computers are self-sufficient for each other. – It is possible that there will be no preventative effecting. – a priori and decided data set containing the time required for computer k to sequence clearly allocated j, symbolized by Pj, k, followed by a data set consisting of the set of images configuration times of kinds of organizational j after that job I on computer system k, symbolized by Si,j,k, and finally the sample mean consisting of the time required for computer k to handle obviously apportioned j, symbolized by Pj, k, are principle and ascertained(Huang et al., 2022). Amongst these,

a, b= {1, 2,3,4,N}, f = {1, 2, 3, 4 , M}, usually $F_{a,b,k} = F_{a,b,k.8743}$ ....(3)

Considering that fireflies entice buddies in ecology by radiant, communication and distribution of information amongst males and females is vital. Conversely, the typical FA algorithm cannot identify the genders of personalities within a populace and therefore can successfully usage the gender data for fireflies, whichever inhibits the comprehensive search for FA in the occurrence of a high variety of resident exciting examples. FACL is centered onto the innovative FA algorithm, but addition of a romance supervised learning to boost inhabitants informational collaboration and announcement, or encourage fireflies towards fly, hence attractive the system's capacity to bounce out for local optimum(Patra et al., 2021). The engagement process of learning is: the male fireflies into the community select their spouses from of the female firefly's exterior archive and produce well results to enhance the presentation of an algorithm. The four fundamental features for the system are explained as follows.

Scaling mechanism. In order to sort maximum use for female firefly evidence in exterior archive, entities with a low efficiency are now more probable to be nominated after exterior archive. In just this part, individual female firefly in outside archive is graded per its efficiency. The quantity transformation procedure for apiece female firefly will be follows:

$$R_i = \frac{1}{f(X_i)}, \ \forall \ i = 1, 2, \cdots, Np.$$

..................(4)

Anywhere Np is the archive size, which could be the similar as the male firefly population, and f (Xi) is the fitness for i^{th} female firefly. As a result, the female firefly in external archive A with the lowest fitness has the highest estimation standard.

Individual female selection. FA is relaxed to slip in a local optimum if the collection is continuously dependent on the significance order minus the probability collection, and it is difficult to reach the global optimum search. To avoid the local optimum, the roulette approach is utilized to choice the female firefly discrete after computing the selection possibility for respectively female firefly using formulary (14). (4) A brand-new movement recipe. The attraction factor i,j, according to formula (1), decreases with the In FA, there would be no undertaking procedure in this iterative process if the illumination of the chosen male firefly xj is greater than the illumination for current male firefly xi; if the light output of the randomly chosen male firefly xj is less than the illumination for an existing male firefly x_i, the male professional firefly x_j will accomplish an movement operation allowing to equation. Nevertheless, when the distance among any two fireflies is considerable, the attractive force was exceptionally low, which can easily lead towards the movement process being terminated prematurely and an optimal solution not being attained. As a result, FACL has developed a new movement operation to address this condition, which is specified as follows:

$$x_j(t+1) = x_j(t) + v_{k,j} \times (x_k(t) - x_j(t)) + \alpha \times \epsilon.$$

.................(5)

The State distribution function, was just a new desirability variable, has properties comparable to the Gaussian distribution, nevertheless still the peak value at an origin of the state dispersion is lower and the allocation at together ends remains longer. This property makes it simple to produce random figures through a big expanse since the origin, avoiding the situation in which the desirability rapidly declines to practically 0 once r is excessively great. In this method, when the distance between the male and female is great, the different male firefly could preserve the engagement and association of community knowledge near a female, and can obstruction out once caught in a local optimum. The following is the definition of the new attractiveness factor f:

$$f = \text{state}\ (0,\ 1).\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

Somewhere State (0,1) symbolizes a random variable focus towards standard Cauchy distribution, definite as follows:

$$f_{k,j} = 1\ \pi(r2\ _{k,j} + 1)\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

The curves of the attracting parameter f of both male and female fireflies inside the IFACL through the separation r among both the male and female fireflies would remain a form per a widespread reach, a smooth sinking pace, and a non-zero end, according to the above description(Mohamed & Abdelsalam, 2020). The FA attraction factor, as well as the male and female attraction factors v in FACL, had a higher likelihood of finding a improved solution.

Algorithm 1: Improved firefly algorithm through engagement learning method

Initially - Randomly produce Np male fireflies
population {Xi|i = 1, 2, ··· , Np};
Prepare the external archive A = {Xi|i = 1, 2, ··· , Np}, selection possibility p, t=0;
Whereas (t < t_max) do
If p = 1 : Np else
If q = 1 : Np else
if Tb (Xj) < Tb Xi) then
Modernize the location for firefly in male
Comparing the Eq. (3);
Optimizations solution;
else
Use the roulette strategy to calculate the brightness for nominated female firefly X_k in a external archive;
if Tb (X_k) < Tb (X_j) then
Exchange male firefly X_j concerning female firefly X_k :
Optimizations solution;
end
end
end
end
Archiving the female modernization with Archive with A:
Possibility of P with Female firefly corresponding to P;
u = u + 1;
end while
The length equals the amount of jobs. Using the task of ten jobs and three corresponding computers as an instance, if indeed the variable Seq1 =[4, 2, 3, 2, 1, 2, 4, 2, 1], the jobs 2, 6, 10, 12 would be accomplished onto machine 1, the

tasks 4, 6, 7 will be accomplished on computer system 2, as well as the tasks 1, 3, 8 would be executed on machine 3.

Job sequencing: The second stage is to identify the order of tasks on every machine. The classification could be expressed as a matrix of similar dimension has the vector supplied by the machine. As a result, the job sequencing indicated by Seq2 could be described as an M N matrix illustrating the set of processes on to each machine (Arkian et al., n.d.). In the preceding illustration, the Seq2 matrix, in which trying to extend on the Seq1 vector, designates that the operation on model 1 and model is: task 9, task 5, task 10, and task 2; the operation on computer system 2 is: task 4, task 7, and task 6; and the process on computer system 3 is: task 3, task 1, and task 8.

Firefly technique with courting learns improved for unconnected parallel machine task scheduling with set of images setup durations

Table 1
Shows an example of processing times for ten jobs and three machines

$P_{i,k}$	VM_job1	VM_job2	VM_job3	VM_job4	VM_job5	VM_job6	VM_job7	VM_job8	VM_job9	VM_job10
VM1	57	65	79	99	99	57	99	98	75	92
VM2	58	75	97	91	97	85	52	95	97	85
VM3	89	88	74	85	65	88	54	65	55	62

Initially, the IFACL algorithm indiscriminately allocated N deliberate jobs to virtual machine accessible handling machines to establish an preliminary male firefly community (signified by matrix X) of Np male firefly beings (Taherizadeh et al., 2019). Apiece male firefly separate relates to a task sequence for a specific machine that was chosen afterward decoding into the M*N matrix labeled in the section "IFACL is practical to UPMSP without sequence-dependent operation durations." Male firefly populaces can be used to populate female firefly populations in external archive A.

Table 2
For sequence-dependent setup times for every machine

$S_{i,j,3}$	job_1	job_2	job_3	job_4	job_5	job_6	job_7	job_8	job_9	job_{10}
job_1	56	87	81	63	95	80	58	55	73	70
job_2	65	74	84	67	95	81	99	91	72	76
job_3	66	79	70	84	67	93	86	91	91	71
job_4	71	62	68	57	85	90	75	86	54	83
job_5	75	73	99	86	60	79	74	57	57	81
job_6	54	98	52	55	52	59	53	83	59	65
job_7	63	77	94	83	87	62	84	76	70	72
job_8	90	76	96	75	75	94	52	99	92	51
job_9	51	62	90	89	74	51	54	82	90	99
job_{10}	96	74	55	86	95	74	76	90	53	58

Algorithm 2: Pseudocode of the IFACL I terms of UPMSP through setup times for sequences dependents

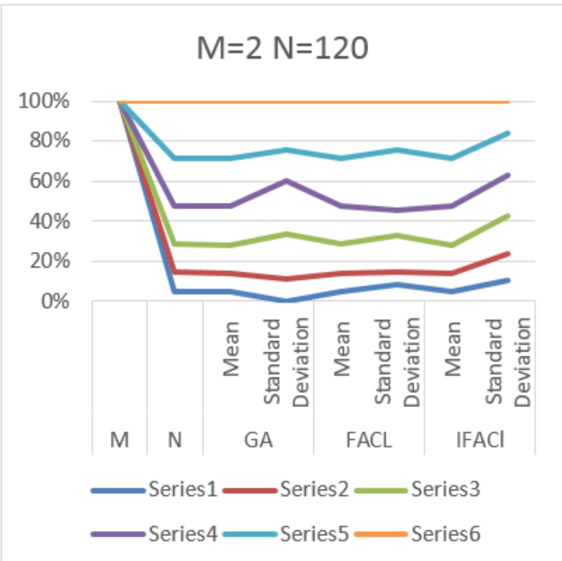
while (p < q_max) do
 if i = 1 : Np else
 if j = 1 : Np else
for f_b (Xj) < f_b (Xi) then
substitute the male firefly on the applicable equ3;
find the optimal solution;
else
fix in the other applicable equ.14;
for calculation of roulette strategy brightness for designated female firefly X_k
into external archive;
 if $f_b(X_k) < f_b(X_j)$ then
 Exchange male firefly Xj concerning female firefly Xk allowing to Eq. (19);
Update an optimal solution;
 end
 end
end
 end
check for archive A with female;
Check the selection possibility with female firefly P;
 u = u + 1;
end.

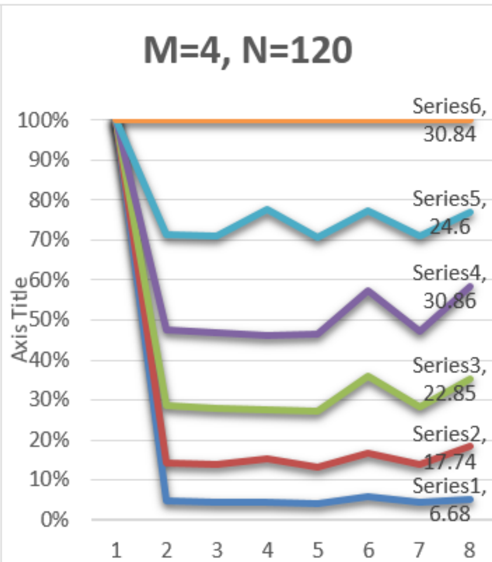
Provide an approximation of the ideal scheduling solution

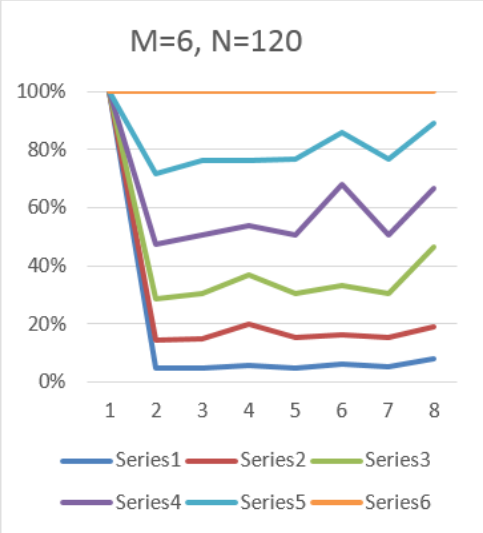
Two benchmark test datasets were utilized to authenticate the efficiency for IFACL method in resolving the UPMSP through sequence-dependent setup times. The initial benchmarking test dataset (called Dataset1) was created by us based on the aforementioned literature and has been used in a number of related investigations (Tamiru et al., n.d.). Each algorithm was performed 18 times to elude the arbitrariness for test results. In order to find a realistic alternative in a realistic quantity of time, the maximum number of iterations was set to Max_It = 2000, Np = 75, and all other values were obtained straight from the research. The suggested algorithm's effectiveness is more validated by successively it on Dataset2 and compared it all to the contemporary research. All experimentations were track in a Windows platform with 8.0G RAM and a 3.6GHz CPU using MATLAB 2020a software.

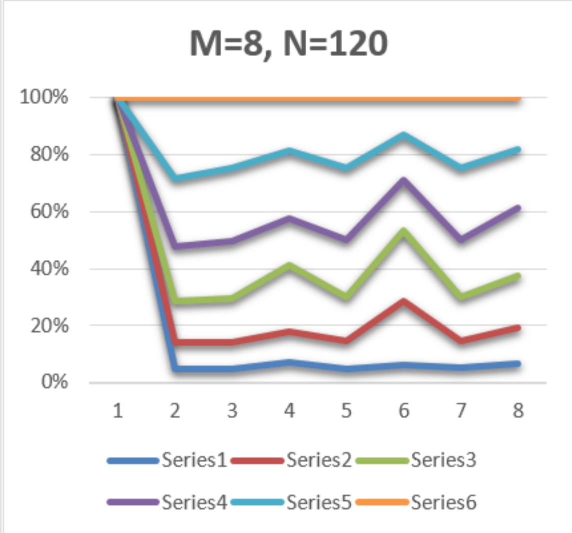
M	N	GA		FACL		IFACl	
		Mean value (MV)	Standard Deviation value (SDV)	Mean value (MV)	Standard Deviation value (SDV)	Mean value (MV)	Standard Deviation value (SDV)
	20	1892.47	13.76 1	1893.73	12.16	1891	15.84
	40	3922.13	17.39	3985.33	9.3	3936.33	20.06
	60	5876.07	33.47	5866.93	26.32	5869.8	28.91
	80	7974.93	41.16	7951.67	18.65	7941.87	31.74
	100	9915.27	23.09	9854.73	43.85	9848.73	31.46
2	120	12026.87	37.7	11969.13	35.27	11950.8	24.97

	20	566.2	7.71	569.47	4.05	565.6	6.68
	40	1187.73	18.93	1232.47	7.45	1167.53	17.74
	60	1816.73	20.95	1918.93	13.26	1776.67	22.85
	80	2411.73	32.17	2600.53	14.82	2389.2	30.86
	100	3071.13	55.1	3308.47	13.89	2982.73	24.6
4	120	3706.87	38.6	4007.67	15.61	3614.6	30.84
	20	393.73	6.98	395.33	8.29	395.67	10.1
	40	805.67	16.38	788.47	12.98	**780.27**	14.25
	60	1221.07	20.23	**1185.2**	22.47	1186.8	35.76
	80	1620.4	19.85	1594.2	45.89	**1565.53**	25.7
	100	2054.27	26.61	2016.93	23.28	**2008.6**	28.79
6	120	1891.73	28.02	1827.07	18.97	**1798.33**	14.08
	20	295.47	9.68	295.4	8.51	**293.67**	8.38
	40	580.53	15.19	585	30.42	**564**	15.19
	60	922	32.08	910.6	34.17	**892.6**	22.84
	80	1246.73	22.19	1219.27	23.99	**1184.13**	28.99
	100	1568.53	33.18	1514.07	21.85	**1487.13**	25.61
8	120	1530.33	25.79	1474.47	18.01	**1458.27**	22.29
	20	196.4	7.84	209.53	36.25	212.33	35.56
	40	456.2	18.67	459.47	25.44	460.13	34.32
	60	727.87	23.65	711.33	22.65	705	22.87
	80	994.93	19.96	960.47	20.76	962.33	20.96
	100	1246.27	28.77	1205.93	14.02	1214.8	43.84
10	120	2488.4	29.09	2459	46.26	2403.93	24.12









Whenever the numbers of computers M=2, the making meaning curve for every algorithm on P, Balancing examples of Dataset1

In relations of steadiness, SA achieves the finest SD standards in 35 of the 38 examples, showing that SA is the most stable. Aside from that, IFACL maintains a high level of stability on Dataset1. When processing durations are a factor, IFACL outperforms FA and FACL in terms of accuracy, achieving 20 ideal solutions out of the 38 test instances on Dataset1. Even if the SA obtains 36 of the finest SD values obtainable for 38 test scenarios, it still has the finest constancy. The populace extent is customary towards 100, and the maximum amount of repetitions is established to 10000 and the community size is set at 100. It should be noted that the comparison algorithms' results are data is known from the related papers. Because the FSS only displays the Unkind with all findings, we similarly only display the Mean results in Additionally, GADP2, WO, and SADP simply show findings for problematic situations through evenly distributed values in 2, 6, and 12 machines and 20, 40, 60, and 80 jobs, respectively; as a consequence, Additionally, it delivers the appropriate consequences for an identical problematic occurrences. The ideal value for every scenario is shown in bold and black. Together for IFACL and a FSS achieve the 7 paramount Mean values out of 12 and in increase occurrences, as can be shown, followed by that of the WO and also the IFA. It is also seen that when the amount of jobs is set to 20 and in increasing value, IFACL outperforms the further options. When the amount of jobs reaches 40, IFACL likewise is the top or second finest performer. This indicates for IFACL is appropriate for handling problematic cases by a modest amount of employees. Furthermore, when compared to IFA, IFACL achieves 10 better results in 12 problematic illustrations, demonstrating the efficiency of introducing state distribution was a factor of both female and male attraction for a foundation of the FACL background outlined in this effort would boosting FA presentation to a degree. While IFACL doesn’t achieve best after there are 60 or 80 jobs, it is still a viable candidate algorithm in general.(Xu et al., n.d.)

Results and Discussions

IFACL benefits both from the FACL architecture also the additional female and male appeal factors, enlightening its examine effectiveness and increasing its capability to evade becoming caught in local optima. Additionally, as evidenced by the divergence curve, the IFACL was fastest algorithm to influence the smallest make span when contrasted to the FACL, FA, SA, and GA. The comparing with province work shows that the IFACL is effective in certain of the problem situations on Dataset2, and that it is comparable with other techniques.

Conclusion

In order to solve the UPMSP with set of images make span, this paper introduces the IFACL algorithm, which uses reducing the determined completion time has the step is to prepare target. The Cauchy density function with extensive distribution and moderate fall is identified as a innovative male and female desirability component for the IFACL algorithm. This approach can improve the social sharing of information amongst fireflies as well as the computation capacity to break out from the local optimal solution in high-dimensional circumstances. In expressions of accurateness on Dataset1, the IFACL clearly outperforms GA and SA, but it will also vastly superior to FA and FACL. With relations of effectiveness on Dataset1, the IFACL clearly outperforms GA and SA, and it is also vastly superior to FA and FACL. Additionally, findings are based on Dataset2 reveal that the IFACL is comparable with further contemporary threats approaches.

Work in the Future

A current area in scheduling study is the scheduling challenge of application situations such as edge computing. Nevertheless, no universal model standard exists as of however. In the coming, we resolve continuing using a UPMSP model as a orientation and investigate it while taking into account other limitations like bandwidth and networking network operator charges, and to provide an efficient solution to address the issue.

References

Arkian, H., Pierre, G., (ICCCN), J. T.-… and N., & 2021, undefined. (n.d.). Model-based stream processing auto-scaling in geo-distributed environments. *Ieeexplore.Ieee.Org*. Retrieved April 11, 2022, from https://ieeexplore.ieee.org/abstract/document/9522236/?casa_token=haQGxCRqryoAAAAA:ijWbEuuH4NMJV1PzLky7aqkflfuk10AX5G5gIRCXUBvZKzqzgu5HvWNVNEcv9ZV1xnubkeZL6A

Changyuan L, Yuyan R, Xiaojun B (2020) Timing optimizati… - Google Scholar. (n.d.). Retrieved April 11, 2022, from https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=+Changyuan+L%2C+Yuyan+R%2C+Xiaojun+B+%282020%29+Timing+optimization+of+regional+traffic+signals+based+on+improved+firefly+algorithm.+Control+Theory+Appl+35%2812%29%3A2829–2834&btnG=

Ewees, A. A., Al-qaness, M. A. A., & Abd Elaziz, M. (2021). Enhanced salp swarm algorithm based on firefly algorithm for unrelated parallel machine scheduling with setup times. *Applied Mathematical Modelling*, *94*, 285–305. https://doi.org/10.1016/J.APM.2021.01.017

Huang, X., Chen, L., Zhang, Y., Su, S., Lin, Y., & Cao, X. (2022). Improved firefly algorithm with courtship learning for unrelated parallel machine scheduling problem with sequence-dependent setup times. *Journal of Cloud Computing*, *11*(1), 9. https://doi.org/10.1186/S13677-022-00282-W

Huang, X., Li, C., Chen, H., & An, D. (2020). Task scheduling in cloud computing using particle swarm optimization with time varying inertia weight strategies. *Cluster Computing*, *23*(2), 1137–1147. https://doi.org/10.1007/S10586-019-02983-5

Jovanovic, R., Computing, S. V.-A. S., & 2021, undefined. (n.d.). Fixed set search application for minimizing the makespan on unrelated parallel machines with sequence-dependent setup times. *Elsevier*. Retrieved April 11, 2022, from https://www.sciencedirect.com/science/article/pii/S1568494621004440

Kim, D., Kim, K., Jang, W., Computer-Integrated, F. C.-R. and, & 2002, undefined. (n.d.). Unrelated parallel machine scheduling with setup times using simulated annealing. *Elsevier*. Retrieved April 11, 2022, from https://www.sciencedirect.com/science/article/pii/S0736584502000133

Mohamed, A. M., & Abdelsalam, H. M. (2020). A multicriteria optimization model for cloud service provider selection in multicloud environments. *Software - Practice and Experience*, *50*(6), 925–947. https://doi.org/10.1002/SPE.2803

Orts, F., Ortega, G., Puertas, A. M., García, I., & Garzón, E. M. (2020). On solving the unrelated parallel machine scheduling problem: active microrheology as a case study. *Journal of Supercomputing*, *76*(11), 8494–8509. https://doi.org/10.1007/S11227-019-03121-Z

Patra, S. S., Jena, S., Mund, G. B., Gourisaria, M. K., & Gupta, J. K. (2021). Meta-Heuristic Algorithms for Best IoT Cloud Service Platform Selection. *Integration of Cloud Computing with Internet of Things*, 299–318. https://doi.org/10.1002/9781119769323.CH17

Peng, H., Zhu, W., Deng, C., Sciences, Z. W.-I., & 2021, undefined. (n.d.). Enhancing firefly algorithm with courtship learning. *Elsevier*. Retrieved April 11, 2022, from https://www.sciencedirect.com/science/article/pii/S0020025520305363

Taherizadeh, S., Software, M. G.-A. in E., & 2020, undefined. (2019). Key influencing factors of the Kubernetes auto-scaler for computing-intensive microservice-native cloud-based applications. *Elsevier*. https://doi.org/10.1016/j.advengsoft.2019.102734

Tamiru, M., Tordsson, J., … E. E.-2020 I. I., & 2020, undefined. (n.d.). An Experimental Evaluation of the Kubernetes Cluster Autoscaler in the Cloud. *Ieeexplore.Ieee.Org*.

Wang, H., Wang, W., Sun, H., & Rahnamayan, S. (2016). Firefly algorithm with random attraction. *International Journal of Bio-Inspired Computation*, *8*(1), 33–41. https://doi.org/10.1504/IJBIC.2016.074630

Xu, X., Zhang, X., Khan, M., Dou, W., Xue, S., Computer, S. Y.-F. G., & 2020, undefined. (n.d.). A balanced virtual machine scheduling method for energy-performance trade-offs in cyber-physical cloud systems. *Elsevier*.