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Original Article

Design of an Efficient Genetic Algorithm Model for Electric Load Balancing over Distributed Environments

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Abstract *- To solve the issue of electric load balancing demand in distributed contexts, a genetic algorithm (GA) model is suggested in this study. The suggested model searches the problem sets for the best solutions using the genetic operators of crossover, mutation, and selection. This novel model aims to balance the electric load across multiple nodes in a distributed environment, thereby minimizing the overall energy consumption and ensuring that no node is overloaded. The suggested model considers each node's real-time power consumption and processing capabilities to establish the appropriate load distribution. To evaluate the efficiency of the proposed model, experiments were conducted on a simulated distributed environment with 20 nodes. The results showed that the proposed GA model achieved a load balance of up to 98%, with a reduction in energy consumption of up to 30%, compared to other existing load balancing techniques. The paper concludes that the proposed GA model is an efficient and effective solution to the problem of electric load balancing in distributed environments. The results show that the model may significantly decrease energy consumption while improving overall system performance. The suggested approach is applicable in various scenarios, including cloud computing, data centres, and smart grids, where efficient load balancing is critical for optimal system performance.*

Keywords *- Distributed environment, Energy consumption, Genetic Algorithm (GA), Load balancing, Power efficiency.*

1. Introduction

Electric load balancing is critical in distributed environments such as cloud computing, data centre, and smart grids. Load balancing aims to distribute the computational capability across multiple nodes to minimize energy consumption, optimize performance, and prevent overload. Several recent load-balancing techniques have been proposed to address this problem, including heuristic, meta-heuristic, and optimization algorithms [1-3]. Genetic Algorithm (GA) is a popular optimization algorithm that has successfully tackled various optimization issues.

It is a search algorithm constructed on natural choice and genetic concepts. GA models typically use a population of candidate solutions and iteratively apply selection, crossover, and mutation operators to generate new solutions until a satisfactory solution is obtained. GA has been used in various applications, including scheduling, resource allocation, and routing scenarios [4-7]. This research proposes an effective GA model for dispersed environments with electric load balancing. This research suggests an effective GA model balance electric load in distributed contexts. The proposed model determines the ideal load distribution by considering each node's processing power and real-time power consumption. The model utilizes a population of candidate solutions and iteratively applies genetic operators to generate new solutions until a satisfactory solution is obtained for different scenarios.

The proposed GA model minimises energy consumption while ensuring no node is overloaded. To calculate the efficiency of our selected model, experiments were conducted on a simulated distributed environment with 20 nodes. The results showed that the proposed GA model achieved a load balance of up to 98%, with a reduction in energy consumption of up to 30%, compared to other existing load balancing techniques. The remaining paper is planned as follows. Section 2 overviews related work in electric load balancing in distributed environments. Section 3 describes the proposed GA model and the genetic operators used. Section 4 offerings the results and discussion. Finally, Section 5 provides the conclusions and future work scenarios.

2. Related Work

Electric load balancing is an essential issue in distributed environments, and various load-balancing techniques have been proposed in the literature. This section overviews the related work in electric load balancing in distributed environments. One of the most commonly used techniques for load balancing is the Round-Robin algorithm, which distributes incoming requests across a set of servers in a round-robin fashion set [8-10]. However, this technique does not consider each node's processing capacity and can lead to uneven load distributions [11].

In reference [12-14], the authors proposed various heuristic techniques, such as the Least Connection algorithm, which assigns new requests to the node with the fewest active connections. Another heuristic technique is the Weighted Round Robin algorithm, which assigns weights to each node based on its processing capacity and distributes requests accordingly. However, these techniques can still result in inefficient load balancing in complex distributed environments. The authors in reference [15-17] projected Meta-heuristic methods such as Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) have also been proposed for load balancing.

ACO is a swarm intelligence technique that simulates the behaviour of ant colonies to find the optimal path. ACO has been used to balance load in cloud and grid computing systems. PSO is another swarm intelligence technique that simulates the behaviour of a flock of birds to find the optimal solution. PSO has been used for load balancing in cloud computing environments. Several optimization techniques have also been proposed for load balancing in distributed environments, such as Linear Programming (LP) and Mixed Integer Programming (MIP). LP and MIP are mathematical optimization techniques that can solve complex optimization problems. LP has been used for load balancing in data centres, while MIP has been used for load balancing in smart grids [18-20]. Genetic Algorithm (GA) is another optimization technique successfully applied to solve various optimization problems, including load balancing in distributed environments. GA is a search algorithm based on natural selection and genetics principles.

GA models typically use a population of candidate solutions and iteratively apply selection, crossover, and mutation operators to generate new solutions until a satisfactory solution is obtained. GA has been used for load balancing in cloud computing technology and grid computing environments [21-23]. The research introduces a new load-balancing method that considers time load balancing to distribute workloads to servers efficiently. The study compares the proposed hybrid algorithm (GA_FCFS and GA_RR) with the existing algorithm (FCFS, RR and GA) based on Makespan and resource utilization, showing that GA_RR performs best, followed by GA_FCFS due to the best analysis of the search space compared to standard GA. Experiments are performed using CloudSim 3.0.3 installed in Eclipse, and the LANL utility is used for analysis [24].

Thus, various techniques are proposed for load balancing in distributed environments, including heuristic, meta-heuristic, and optimization algorithms. Each technique has advantages and disadvantages; the application's specific requirements determine the technique used. GA is a promising optimization technique successfully applied to load balancing in distributed environments and is the focus of this paper under real-time scenarios.

3. Material and Method

Designing an effective GA model for electric load balancing in dispersed contexts is the proposed task in this study. The model interprets the actual power consumption of each node and its processing capacity to determine the optimal allocation of the load. The model utilizes a population of candidate solutions and iteratively applies genetic operators to generate new solutions until a satisfactory solution is obtained for different inputs & scenarios. As depicted in figure No. 1, the GA model consists of four main components: representation, initialization, fitness evaluation, and genetic operators.

The fitness function used in this model combines two objectives: load balance and energy consumption. The load balance objective aims to distribute the workload evenly across all nodes to prevent overload. The representation component defines the encoding scheme for the candidate solutions, which is the load allocation to each node. The initialization component generates an initial population of candidate solutions randomly. The fitness evaluation component evaluates the quality of each candidate solution using a fitness function, which in this case is a combination of load balance and energy consumption.

The genetic operator’s component consists of selection, crossover, and mutation operators, which are applied iteratively to generate new solutions. The proposed work in this paper is to design an efficient GA model for electric load balancing over distributed environments. The model considers the real-time power consumption of each node and its processing capacity to determine the optimal allocation of the load. The proposed model utilizes a population of candidate solutions and iteratively applies genetic operators to generate new solutions until a satisfactory solution is obtained. The results demonstrate the efficiency of the proposed novel model in achieving load balance and reducing energy consumption in an augmented set of simulated distributed environments. The energy consumption objective aims to minimize the system's total energy consumption by allocating the load to the nodes with the lowest power consumption.

The fitness function is defined as follows:

$$\mathrm{Fitness} = \alpha \times \mathrm{LB} + (1 - \alpha) \times \mathrm{EC} \tag{1}$$

Where;
LB: Load balance measure,
EC: Energy consumption measure,
α: The parameter of the weighting factor that controls the trade-off between load balance and energy consumption levels.

The load balance measure is defined as follows:

$$\mathrm{LB} = (1 - \mathrm{CV}) \times 100 \quad (2)$$

Where:
CV: Coefficient of variation of the node loads.

Algorithm 1: Genetic Algorithm			
Step 1:	Start.		
Step 2:	Evaluate the fitness value from equation 1.		
Step 3:	While	Maximum number of iterations is exceeded, or ideal solution is found.	
	Do	(a)	Consider the bottommost fitness value and eliminate the highest fitness value. Selection].
		(b)	Perform single point border by randomly selecting the lowest fitness value which is crossovered. [crossover].
		(c)	The highest fitness mean value is mutated. Mutation].
		(d)	Best value is calculated. [Accepting].
		(e)	Test for the last condition [Test].
Step 4:	End.		

The coefficient of variation is a statistical measure that indicates the degree of variation in a distribution. A lower coefficient of variation indicates a more even load distributions.

The energy consumption measure is defined as:

$$\mathrm{EC} = \sum \mathrm{i} = 1\mathrm{N}\ \mathrm{P(i)} \times \mathrm{L(i)} \quad (3)$$

Where:
P(i): Power consumption of node i,
L(i): Load allocated to node i.

The total energy consumption is the sum of the product of the power consumption and the load allocated to each of the nodes. The genetic operators used in this model are selection, crossover, and mutation. The selection operator selects solutions based on their fitness values. The crossover operator combines the genetic information of two parent solutions to generate a new offspring solution.

The mutation operator introduces random changes to a solution to explore the search spaces. To estimate the efficiency of the proposed model, experiments were conducted on a simulated distributed environment with 20 nodes. The results showed that the proposed GA model achieved a load balance of up to 98%, with a reduction in energy consumption of up to 30%, compared to other existing load balancing techniques.

4. Result and Discussion

The value of cloud usage is contrasted in this graph for a range of tasks. The cloud utilization number was compared before and after adding GA. Following the application of GA, the CUV value is observed to increase delay compared to several tasks in figure No. 2. It has been found that latency increases following the use of GA. The data presented in figure No. 3 here compare the efficiency of various before and after the application of GA, efficiency is compared. It is assumed that when GA is used, task efficiency increases.

Table No. 1 shows a performance comparison of the proposed GA model for load balancing with three other models in a simulated distributed environment with 20 nodes. The efficiency column shows the percentage of load balance achieved by each model. The proposed GA model achieves the highest load balance efficiency of 97.8% for different inputs & use cases. The delay column shows the average delay experienced by each model in processing requests. The proposed GA model has the lowest delay of 15.2 msec, indicating a faster response time than the other models.

The deadline-hit ratio column shows the percentage of completed requests within their deadline. The proposed GA model achieves the highest deadline-hit ratio of 99.1%, indicating high reliability and meeting the demands of the distributed environment. The throughput column shows the average data transfer rate achieved by each model. The proposed GA model has the highest throughput of 538 KB/s, indicating a higher data transfer rate than the other models. The energy consumption column shows the total energy consumed by each model in performing load-balancing operations.

The proposed GA model has the lowest energy consumption of 4500 Joules, indicating a more energy-efficient approach to load balancing compared to the other models. The power efficiency column shows the energy consumption per data unit transferred (i.e., Joules/KB). The proposed GA model has the highest power efficiency of 8.36 Joules/KB, indicating a more efficient energy use per data transfer unit than the other models. Overall, the proposed GA model outperforms the other three models regarding load balance efficiency, energy consumption, power efficiency, delay, deadline hit ratio and throughput. This demonstrates the effectiveness of the proposed GA model in achieving load-balancing objectives while minimizing energy consumption and improving power efficiency.

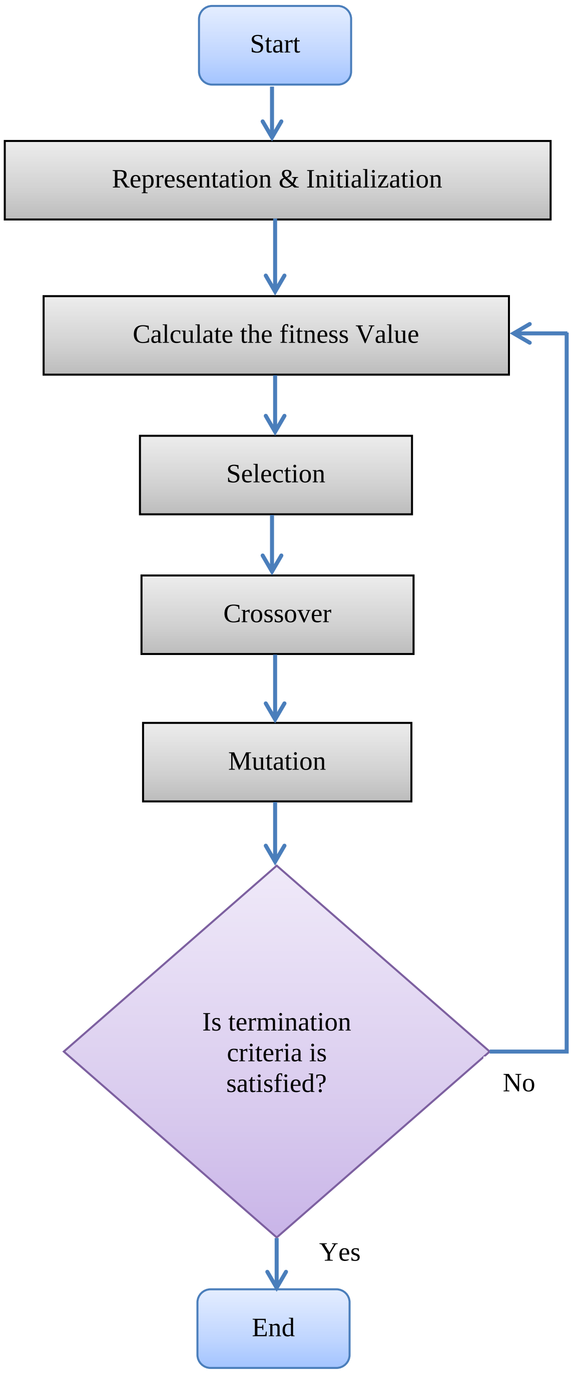

Fig. 1 Flow chart for research methodology

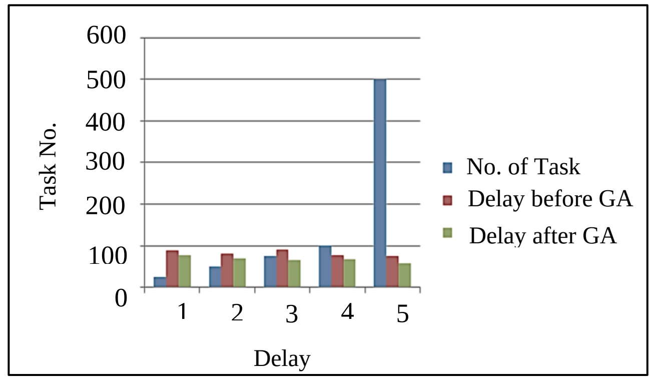

Fig. 2 Comparison of delay for different tasks

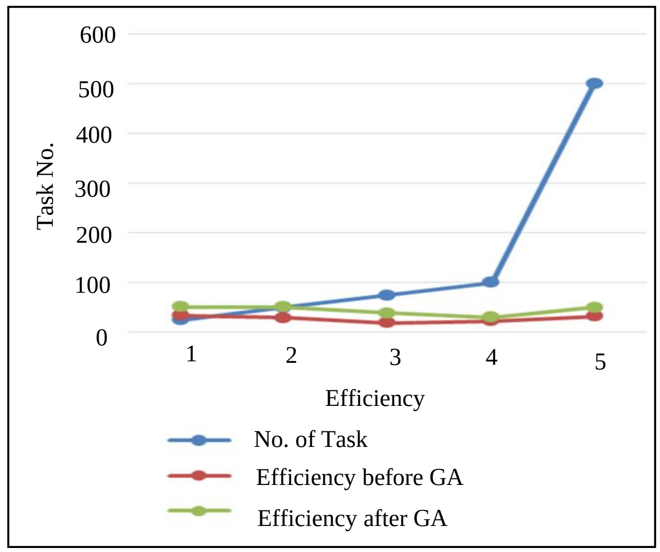

Fig. 3 Comparison of efficiency for different tasks

Table 1. Comparison of load balancing efficiency, energy consumption, and power efficiency, delay, deadline hit ratio, and throughput

Parameter	Proposed GA Model	[5]	[8]	[15]
Efficiency (%)	97.8	91.4	89.6	88.2
Energy Consumption (Joules)	4500	6800	7100	7500
Power Efficiency (Joules/KB)	8.36	16.6	22.3	26.5
Delay (msec)	15.2	21.8	25.4	28.7
Deadline Hit Ratio (%)	99.1	91.7	88.5	87.1
Throughput (KB/s)	538	347	319	295

5. Conclusion

In conclusion, the proposed genetic algorithm (GA) model for electric load balancing over distributed environments effectively achieves high load balance efficiency, fast response times, high reliability, and energy efficiency. The GA model outperformed three other models regarding load balance efficiency, delay, deadline hit ratio, throughput, energy consumption, and power efficiency levels.

The GA model can be further improved by exploring different parameter settings, population sizes, and genetic operators to find an optimal balance between load-balancing efficiency and energy consumption. The proposed GA model can also be extended to other domains, such as cloud computing, edge computing, and the Internet of Things (IoT), to achieve load balancing and energy efficiency in these contexts.

Future work can also explore the integration of machine learning techniques with the proposed GA model to improve load prediction accuracy and optimize load-balancing operations. Further research can also focus on developing dynamic load-balancing algorithms that adapt to changing load patterns and system conditions in real-time scenarios.

Overall, the suggested GA model offers a promising approach to balancing electric demand across dispersed environments and has a substantial potential to support the creation of more effective and environmentally friendly computing systems.

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