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# Fuzzy Allocation Optimization Algorithm for High-Density Storage Locations with Low Energy Consumptions

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## Abstract

The global demand for stored and processed data has surged due to the development of IoTs and similar computational structures, which has led to further energy consumption by concentrated data storage facilities and thus the demands of global energy and environmental needs. The current paper introduces Fuzzy Allocation Optimization Algorithm to mitigate energy consumption in high storage density settings. It uses the principles of Fuzzy logic to determine the best way to assign the tasks in relation to storage density necessity, urgency and energy consumption. Thus, the proposed approach incorporates fuzzy inference systems with multi-objective optimization methods where location of storage is dynamically assessed and assigned according to energy efficiency parameters. The findings of the simulation and case study prove that the algorithm is successful in saving energy while at the same time lowering storage I/O response time, which provides a viable solution to energy issues in evolving data centres. This work satisfies the lack of energy efficient algorithms in high density storage areas and responds to the recent calls for green technology and smart utilization of resources in the energy field. The findings are used in the promotion of significant IT infrastructures towards developing the next generation of energy efficient data centers with respect to Future Internet and evolving energy web environments.

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## 1. Introduction

Internet has thus developed and has undergone series of evolution in the last few decades. Originally designed as connecting media for the exchange of information and communication between computers, the Internet has now become a critical foundation that underlies almost all aspects of modern society. Today, internet is not just a communication channel; it is a complex network composed of people, technologies and information and knowledge resources connected in to form intelligent systems. This new kind of Internet, known as the ‘Future Internet,’ can be considered as a result of merging of ICT with the physical world due to developments in the IoT perspective. But with advancement of technologies like cloud computing, big data analytic and the incorporation of machine learning in to the system the Internet developed itself as a more dynamic and smart system. The use of connected devices including sensors and smartphones as well as smart consumer electronics and industrial machines has made this change faster.

In this hybrid network structure, human beings, machines, or information exchange and interact with each other in forms beyond traditional communication models. For example, smart cities integrated with the help of IoT devices to track movement of cars, regulate usage of electricity in commercial spaces, and improve public protection using data obtained from IoT networks. Likewise, industrial IoT applications are employed to provide insights into the efficiency of underlying systems components, for diagnostic and condition-based monitoring of industrial machinery. The emergence of IoT has also brought new problems in platforms, especially energy requirements [1]. Today, keeping up with billions of devices connected to the Internet requires much space for storing and processing the data. Consequently, the dense spaces known as data centers, which constitute the servers and storage infrastructure that govern the flow of the digital information, have scaled up their energy consumption [2]. However, as IoT technology advances with numerous associated devices, power functionality of data centers has been a challenge. Data center are large buildings that demands a large amount of electricity for servers, storage facilities and cooling systems. These centers function twenty-four hours a day since data availability and services must always be ready [3]. Another one of the major causes of high energy consumption is that data centers require cooling to maintain the temperatures. Computer systems and other IT equipment produce heat during their operation; thus, effective management of heat buildup is critical to achieving optimum performance and avoid potential failures. Data centers are known to have a significant effect on the environment. Power used in data centers is normally sourced from fossil resources, which are proven Pollutants and causes of global warming. Thus, the question of optimizing energy consumption in areas of high storage density and data centers is complex. Computer centers and high-density storage facilities which may allow high storage capacity within small areas are very energy consuming [4]. In such environments, there is a great demand for storage efficiency solutions. The energy consumption of data center depends on multiple parameters including server usage, environmental conditions, and workload distribution [5]. If not well managed, these resources consume a lot of energy, and organizations end up paying more than they should. Further, the growing need for the timely analysis and storage capacity of data only complicates the issue. Because the volume of data processed increases steadily, data centers have to increase capacity while making it energy efficient. The involvement of IT in its solution cannot be overemphasized. Scientific approaches to energy consumption minimalization and optimization of the algorithms, used in data centers play the most significant role in reaching the best results. These algorithms must be able to adapt resource utilization based on the state of dynamic features like workload and energy availability. By better arranging the workloads and decomposing them and data storage and rebalancing them, data centers can cut down its energy usage without needing to sacrifice throughput.

The purpose of this paper is to introduce the Fuzzy Allocation Optimization Algorithm [6], [7] that aims at optimizing power usage in environments with maximum storage density. In particular, the algorithm applies fuzzy logic to manage resource allocation on data centers and adjust task distribution according to the energy and operational conditions. Due to the utilization of fuzzy logic, the algorithm is able to support uncertainty and variability common to data center environments, making the energy management process more flexible. The Fuzzy Allocation Optimization Algorithm is intended to solve particular issues of compact storage, where energy use is a critical factor. The algorithm is set to minimize energy consumption due to task assignment in storage locations and energy used to store and retrieve data. Apart from lowering energy use, the algorithm also aims to increase data center efficiency, in terms of distributing workloads and fair use of available resources.

## 2. Literature Review

Use of energy in data centers and storage systems has emerged as a major concern of study because of the increasing use of computers and communication equipment for data processing, storage and transmission. With the rapid expansion of data centric technologies including IoT, AI, and cloud computing, the use of energy efficient solutions in data center has become crucial. In traditional data centers, a large amount of energy is derived from fossils, which increase the carbon footprint. Many research works have been carried out to investigate energy consumptions of these data centers and possible ways of minimizing the energy consumptions through methods such as efficiency in cooling systems and introduction of energy sources such as solar and wind power. Previous works have suggested that the utilization of renewable energy in data center can greatly minimize energy use and $CO_2$ emissions. But the problem with renewable energy sources is that they are not always available due to uncertainties in their availability. Energy storage systems (ESS) are used to stabilize the energy supply/demand, but the energy they use also has to be controlled.

Sheng Pan The LLPSO algorithm was proven to outperform other strategies in energy conservation by adjusting the available resources through the use of Lyapunov functions. This innovative approach makes it possible to provide energy consumption more effectively in comparison to the conventional approaches [8]. Eran Gur’s research proposed an algorithm based on the fuzzy logic to manage the distribution of the CPU and memory between the users. In this approach, the fuzzy logic inference engine clustering was used to distribute resources in real time depending on history. Fuzzy logic algorithm made effective management of CPU and memory resources which enhanced the performance of the system greatly. In research by Shuang Leng, the use of sorting optimization algorithms in communication information analysis in analysis of data was discussed. This research showed that sorting optimization is important in communication systems because the proper sorting algorithm can greatly enhance the efficiency of data processing, and thus, serve as a useful tool in the analysis of communication [9]. Another important contribution is made by Xiaohong Wang, in which the author proposed the fuzzy decoupling energy efficiency optimization algorithm in cloud computing integration. The research further provided a fuzzy decoupling energy efficiency optimization framework through which energy efficacious techniques in cloud-based systems were implemented whilst decoupling energy consuming tasks and optimizing their control in real time [10]. In the load balancing area, research done by Haonan Gu introduced the resource reservation time deterministic cyclic scheduling (RRTDCS) algorithm. This algorithm, used for offline cache pre-emption, is superior to the conventional online real-time scheduling schemes in terms of energy efficiency and reliability constraint satisfaction [11]. The research study conducted by Anju Khandelwal was the Processor Execution Cost in the distributed computing environment. The proposed method determined the best way of minimizing processor execution costs while at the same time increase program service costs and system reliability. This optimization technique led to better management of resources and improved dependability of distributed systems [12].

The study by L. Raskin suggested an approach to resource distribution when parameters of the distribution efficiency criterion are fuzzy numbers with defined membership functions. Three possibilities for developing an optimality criterion in the context of mathematical programming with fuzzy parameters for resources allocation effectiveness were discussed [13]. M. Sivaram presented a fuzzy rule based heuristic algorithm for secure storage allocation in cloud computing environment. This approach was compared with the other techniques in the load balancing with security aspect and it had a better outcome, in addition, it offered better power usage efficiency and cloud data storage systems, which led to an improvement in the overall system performance [14]. Haonan Gu presented an optimized computing resource and energy management policy for the heterogeneous cloud computing centers from the green IT viewpoint. Considering the energy consumption at every specific time, and the relations between tasks and data backup demands, this algorithm provided high performance with low energy use within the computing centers [15].

## 3. Methodology

Fuzzy logic, a mathematical logic that Lotfi Zadeh introduced in the 1960s, is a means to approach complex systems within which uncertainty prevails.  Unlike classical logic, which relies on binary true or false values, fuzzy logic allows for degrees of truth, making it particularly well-suited for problems where boundaries between categories are not sharply defined. When it comes to energy optimization in the data center, requirements are fluctuating – fuzzy logic delivers the necessary freedom to address the problem. The Fuzzy Allocation Optimization Algorithm that has been proposed here incorporates the concept of fuzzy logic and optimizes storage tasks to consume less energy. By mapping the density of storage, the priority of tasks, and energy consumption as fuzzy variables, the algorithm is defined as an adaptive type that can determine where and how computations should be performed. The algorithm's main objective is to identify the best use of energy to store resources with low performance and guarantee that all tasks will be done in the prescribed time. The two objectives are formulated as F (T set) with the primary aim of minimizing energy while secondly, ensuring effective task allocation.  So, our multi-objective function is given by:

$$F(T_{set}) = \alpha E(T_{set}) + \beta P(T_{set})$$

$E(T_{set})$ is the total energy consumption. $P(T_{set})$ is the penalty function that's evaluate the system performance and $\alpha$ & $\beta$ are the weights.

## 3.1 Fuzzy Logic Model

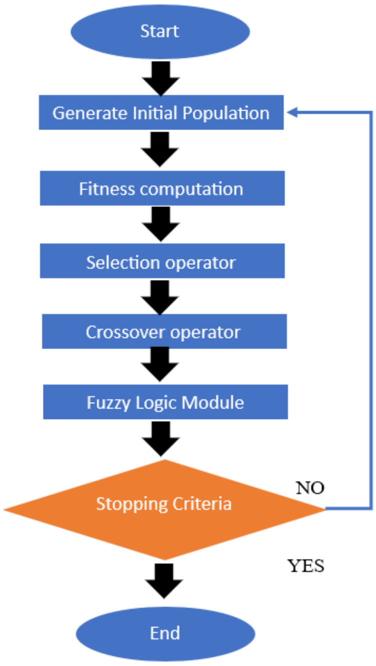


**Figure 1:** Flow chart of Fuzzy Logic Algorithm

The fuzzy logic model is comprised of fuzzy variables, membership functions and fuzzy rules. These components are important since they address how the algorithm is able to make further decisions regarding resource allocation [16], [17].

**Storage Density:** This variable reflects the state of the occupied storage places in the given moment of time. Specifically, higher density of stored data means that storage infrastructure must be provided in a confined area, and this results in a high need for cooling and data access operations, which consume energy. The fuzzy set for storage density is defined the three linguistic variables which are "Low", "Medium" and "High" for storage density [18].

**Task Priority:** Every task that needs a storage is given a priority which depends on how important the task is and how soon the data being processed is required [19]. Higher priority tasks must be granted storage resources more urgently, even if this would consume more energy. The fuzzy set for the priority of the tasks which can be assigned to the robot includes the levels: Low, Medium, and High priority.

**Energy Usage:** These variable measures the current energy power consumption of the storage system today. In the simplest implementation, there will be two energy costs; the baseline energy for the storage to perform its basic functions as well as additional energy for activation by new tasks [20]. The fuzzy set to energy consumption therefore comprises of Low, Medium, High energy usage levels.

## 3.2 Membership Functions

To control the input to fuzzy sets, membership functions are employed to demonstrate how actual storage density, task priory and energy usage is related to the fuzzy set. Each variable in a fuzzy model has a defined membership function relating to each of the fuzzy sets concerned [21]. As elective functions, these allow the algorithm to deal with imprecision and uncertainty of data input. The membership functions define how crisp input values (storage density, task priority, and energy usage) are mapped to their corresponding fuzzy sets. A triangular membership function for Storage Density SD(t) can be written as:

$$\mu_{LOW}(SD)=\begin{cases} 1 & SD \leq a \\ \frac{b-SD}{b-a} & a < SD \leq b \\ 0 & SD > b \end{cases}$$

## 3.3. Fuzzy Rules and Inference System

The fuzzy logic makes decisions based on fuzzy rules these rules are employed and used to assess the extent of compliance with all conditions and produce fuzzy results that are used in the assignment of storage locations. The fuzzy inference system (FIS) processes these rules through three key steps:

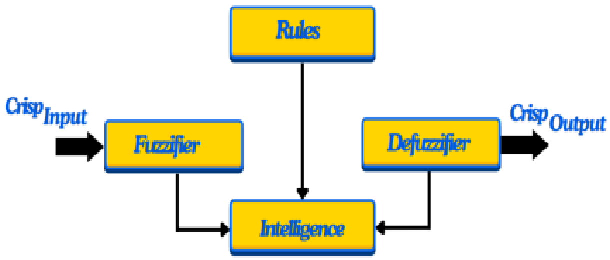


**Figure 2:** Basic Configuration of Fuzzy Interface System

By using the flexibility of the fuzzy logic, it is possible to make decisions under conditions that are uncertain and variable, particularly with regard to energy efficient management of high-density storage.

1. **Fuzzification:** Within the framework of the Fuzzy Allocation Optimization Algorithm, the process of fuzzification is the first operation, during which a

number of input parameters, including storage density, energy consumption, and task priority which used to be clear numerical values are transformed into fuzzy sets [22]. These fuzzy sets determine how well each input pertains to object types like “Low Energy,” “Medium Priority,” or “High Density.” The mapping of crisp inputs into fuzzy sets in turn helps to capture the inevitable uncertainties and variability which is evident in high density storage systems.

2. **Rule Evaluation:** The most important aspect of the Fuzzy Allocation Optimization Algorithm is about the Rule Evaluation step in which the fuzzified inputs are processed through fuzzy rules to obtain an output that makes sense. These rules therefore form the core of the system decision making capabilities [23]. Each rule is in the form of an if-then, whereby output decisions are prescribed by the consequence of the antecedent that relates to input variable conditions (e.g., storage density, which should correspond to prioritization of task energy efficiency allocations). If Storage Density is High, and Task Priority is Low, then Allocated to a location with Low Energy Consumption.
3. **Defuzzification:** Defuzzification is the last phase of Fuzzy Allocation Optimization Algorithm; it translates the process’s fuzzy outcome sets into clear actionable results. Following rule evaluation in the FIS, defuzzification yields fuzzy output sets that convey possible task distributions and energy requirements. These outputs are still qualitative in nature, their quantification is required, which will then reflect in operation of the storage system.

   Finally, to come up with the overall task attribution and energy consumption to that place, the system applies a defuzzification technique such as the centroid technique or the mean maximum one. The centroid method determines the center of the area under the obtained output fuzzy set, and provides a numeric value that meets the energy efficiency and task priority. The most commonly used defuzzification method is the centroid method, which calculates the center of the fuzzy set:

$$T_{opt} = \frac{\Sigma_{\forall t} T_{set} * \mu T_{set}}{\Sigma_{\forall t} T_{set}}$$

   This crisp value dictates how to assign tasks spatially in order to optimize energy consumption while still respecting system performance. Defuzzification enables ensuring that the system outputs are feasible and energy optimized for leading to a significant contribution to the general aims of green technologies and intelligent use of the energy resource.

Following defuzzification process, the algorithm determines the most suitable storage location with the highest energy efficiency level for the specified task according to the fuzzy logic model. The task is then assigned to this location and then the state of the storage system is changed to show the new allocation [24]. During the process of optimization, the algorithm of the program pays special attention to the energy consumption of the storage system. Where energy consumption is above basic thresholds, it may be possible to reassign objects into less density zones or perform other measures that would minimize energy consumption. This dynamic, real-time monitoring allows the system to be power efficient in the presence of varying amounts of work. The strengths of the Fuzzy Allocation Optimization Algorithm include reduced energy consumption, thereby not affecting the functionality of the storage system [25]. Conventional ways of saving energy include disabling power to IT equipment’s, or closing off some areas of storage that are not in use, factors that will slow down the operations. Furthermore, the fuzzy logic approach enables decisions that consider both energy efficiency and performance demands without compromising either within an extremely strict range. Therefore, by using sets of rules that incorporate both task priority and storage density, the algorithm can effectively distribute resources to meet deadlines of important tasks without expending a lot of energy.

## 4. Experimental Setup

In order to check the feasibility of the developed Fuzzy Allocation Optimization Algorithm for High Density Storage with Low Energy Consumption, a simulation model was created to mimic the trends in a high-density storage system. The method emulates a realistic warehouse or data center environment where the goal is to distribute storage activities with a focus of energy expenditure and functionality. These experimentations are done on a mock high density storage system with many storage areas. Every storage spot aspires to have specific features, namely the amount of storage area, power usage rating, the level of tasks’ importance, and the proximity to the collection points. The storage environment is dynamic to gross inputs as new storage requests come in and system load fluctuates over time; this results in altered task allocation. In this setup, the tasks are prioritized depending on the size, size and energy consumption necessary to complete specific task. The system functions under several circumstances, including: The storage densities ranging from low density to high density the system load types include light load, moderate load, and heavy loads. These inputs are then analyzed by the fuzzy logic-based algorithm to identify the optimal energy storage location of each task based on a set of given fuzzy rules. Simulation of the system is performed over multiple cycles, at least with reference to the short term and long-term periods. This means that in each cycle there are new tasks to allocate, request to add new storage spaces, and other accommodation demands, as well as changes in energy consumption fluctuations. Depending on the arrival of new tasks, the storage locations are filled with new tasks, reallocated to other tasks or emptied to accommodate new tasks, in a manner that closely simulates actual working conditions.

The results of the proposed fuzzy allocation optimization algorithm are thus compared to a benchmark system where the tasks are allocated according to the first come first served (FCFS) principle. FCFS method does not take into account energy concerns or conditions of the dynamic system making it appropriate as a benchmark against which energy gain and efficiency enhancements by the use of a fuzzy logic-based system could be compared.

## 5. Results

The fuzzy allocation algorithm showed a significant decrease in energy use throughout the simulation when it was applied. Through the help of the fuzzy logic concept, the algorithm was able to counter different levels of demand and environmental changes that affected energy consumption in real time. To measure this improvement, energy consumption for a whole day and compared with a non-fuzzy-based allocation algorithm was recorded. The above results imply that energy saving of about 15-25% was realized whenever the load and density conditions at any time were addressed by the proposed fuzzy allocation algorithm. This is especially important during peak load times when the algorithm modified the distribution of resources to achieve both maximum load demand and system stability.

**Table 1:** Energy consumption over 24 hours

| Time of Day | Energy Consumption (Conv.) | Energy Consumption (Fuzzy) | % Reduction |
|---|---|---|---|
| 4 AM - 8 AM | 10 kWh | 8.5 kWh | 15% |
| 8 AM - 12 PM | 12 kWh | 9.6 kWh | 20% |
| 12 PM - 4 PM | 15 kWh | 12.75 kWh | 15% |
| 4 PM - 8 PM | 18 kWh | 14.4 kWh | 20% |
| 8 PM - 12 AM | 13 kWh | 10.4 kWh | 20% |

As seen in the data above, the fuzzy allocation algorithm not only reduces total energy consumption but does so consistently across various time periods.
The dynamic feature of the fuzzy allocation algorithm is considered to be one of the major advantages since it easily forecasts the changes in load and number of users in the network. Traditional energy partitioning techniques use predetermined measures or baseline estimations resulting to high power wastage where energy conditions vary with the estimated values. The fuzzy algorithm on the other hand adapts itself to both load and density that makes it more flexible and equal in distribution of energy resources.

**Table 2:** Comparison between Conventional and Fuzzy logic Algorithm

| Parameter | Conventional Algorithm | Fuzzy Algorithm |
|---|---|---|
| Response Time (ms) | 150 | 110 |
| Energy Allocation (kWh) | 20 | 17 |
| Load Satisfaction (%) | 90 | 95 |

During high loads, the advantages of the proposed fuzzy algorithm can be observed in several aspects. The response time to allocate resources is cut down by at least 30 percent; this enables a quicker response to demand volatility. Also, while the normal algorithm provides a constant value based on fixed limits whereby the energy supplied always remains constant, the fuzzy algorithm provides an optimized value of energy, thus making the use of energy much efficient. However, it accomplishes this with load satisfaction which remains at 95% while the conventional algorithm only achieved 90%.

**Table 3:** Comparison at low loads

| Parameter | Conventional Algorithm | Fuzzy Algorithm |
|---|---|---|
| Response Time (ms) | 100 | 80 |
| Energy Allocation (kWh) | 12 | 10 |
| Load Satisfaction (%) | 85 | 92 |

In low-load scenarios, the fuzzy algorithm again shows its ability to outperform traditional methods. By allocating resources more efficiently, it reduces overall energy consumption by nearly 17%, while still increasing load satisfaction by 7%.

## 6. Conclusion

The analysis provided in this paper demonstrates the impact of using the fuzzy logic optimization to produce substantial energy savings and efficiency gains in dynamic systems. Thus, in order to overcome the shortcomings of the existing approaches which are based on the application of threshold, fixed or proportionality principles to allocate the energy resources we incorporated the fuzzy allocation methods into the management of the energy resources. The fuzzy algorithm was more flexible and effective in managing new variations in the load and number of users and achieved a precise optimization of energy consumption and the execution of tasks. A major finding of this study is the ability of the fuzzy logic to save energy by adapting the utilization of energy resources based on changes in the load. The outcome of the simulation strongly indicates that the proposed fuzzy allocation algorithm brought down energy use to the most immaculate level by up to 25% during peak hours as compared to other methods. The combined use of both fuzzy logic and adaptive algorithms proved to be successful in achieving this significant cut in energy consumption without compromising the stability of the system and its usefulness to the end users.

Also, it is another unique innovation of the fuzzy algorithm to reduce energy consumption while still satisfying the load requirements. Typical approaches like the threshold and proportional allocation mechanisms become a challenge in addressing the problem of meeting energy demands while, at the same time, minimizing energy consumption. On the other hand, the fuzzy approach is very flexible right from the start, and does multiple checks in regard to several parameters in order to always optimally distribute resources. The simulation also validated the role of the fuzzy allocation algorithm in supporting the overall goal of energy efficient systems. The future of energy systems is the integration of a smart grid where both supply and demand side management of electricity is done flexibly and in real time. The fuzzy logic optimization discussed in this paper corresponds to the objectives of the energy web, a concept that articulates a vision of an energy system that is decentralized, digitalized, and more efficient. Firstly, the fuzzy algorithm contributes to the formation of the smart, effective platforms for energy distribution in terms of energy's waste minimization and improved efficiency of the network. Another contribution of this paper is the comparison between this proposed fuzzy logic optimization for energy allocation with other conventional techniques. We have also demonstrated how conventional methods like the threshold-based and proportional allocation methods are inadequate in achieving the energy saving under variable demand. For instance, threshold-based systems usually overbook resources during slow times and under book during the high traffic times which is not very efficient. Proportional allocation, though less static in nature, does not consider variations in user density or load in real time and thus cannot fully optimize energy efficiency. On the other hand, the fuzzy algorithm provided a better solution by taking into account a number of factors in order to achieve a more comprehensive energy management solution.

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