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Developing a model for energy-efficient data storage in cloud-based database management systems

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Abstract

The huge growth of digital data has made cloud-based database management systems (DBMS) face serious problems, especially when it comes to speed, scalability, and energy use. Traditional ways of keeping things are based on speed and quantity, not on how long they will last. There is a model in this work that combines dynamic compression, smart resource sharing, and faster query processing. Using mathematical formulas turns energy use into an optimization problem, it accurately weigh the pros and cons of different options. Experiments study show that energy savings are always between 32.8% and 34.2%, even when different tasks are used.

Subject Classification: *68P15, 97P30.*

Keywords: *Energy-efficient storage, Cloud DBMS, Optimization, Scalability, Mathematical modeling, Sustainability.*

I. Introduction

Cloud platforms are being used more and more to store and retrieve large amounts of data, which has raised worries about both speed and energy economy [1, 2]. As businesses grow their data operations in many areas, like healthcare, banking, and e-commerce, they need storage models that can grow with their

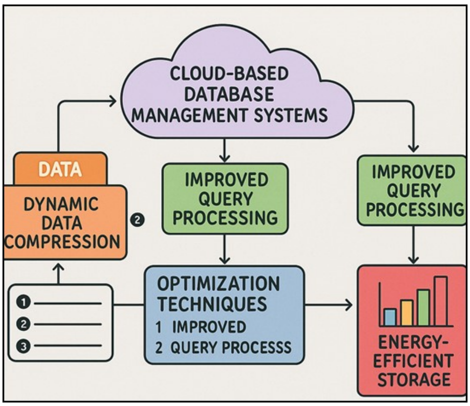

Figure 1
Architecture of Energy-Efficient Data Storage Model in Cloud-Based DBMS

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needs and last for a long time [3, 4]. Traditional ways of storing databases tend to focus on speed and volume, without taking into account the economic and environmental effects of using a lot of energy (show in Figure 1). This has made things less efficient, caused costs to go up, and left big carbon traces [5]. Because of this, energy economy in cloud-based DBMS is becoming an important area of study that combines ideas from optimization, remote computing, and building systems that last [6, 7].

Cloud companies can help organizations save money and the environment by eliminating superfluous storage, improving access patterns, and lowering hardware costs [8, 9]. We can also calculate energy trade-offs using mathematical models and computer technologies. This maintains storage performance.

II. Proposed Model for Energy-Efficient Storage

The suggested model includes dynamic data compression, energy-aware storage distribution, and better query handling. It cuts down on unnecessary work, spreads the load across multiple computers, and changes how resources are used based on changes in the task [10].

Total Energy Consumption:

$$E_{total} = \Sigma \left(E_{comp}, i + E_{stor}, i + E_{comm}, i\right) \tag{1}$$

Storage Energy:

$$E_{stor}, i = P_{stor}, i \times T_{stor}, i \tag{2}$$

Computation Energy:

$$E_{comp}, i = P_{CPU}, i \times T_{comp}, i \tag{3}$$

Communication Energy:

$$E_{comm}, i = P_{net}, i \times T_{trans}, i \tag{4}$$

Workload Demand:

$$W_i = \lambda_i \times D_i \tag{5}$$

Resource Utilization:

$$U_i = \frac{W_i}{C_i} \tag{6}$$

Energy Efficiency Metric:

$$\eta = \frac{W_{total}}{E_{total}} \tag{7}$$

Load Balancing Constraint:

$$\Sigma U_i \leq 1$$

Redundant Storage Penalty:

$$E_{redund} = \alpha \times R \tag{8}$$

Objective Function:

$$Minimize\ E_{total} = \Sigma \left(E_{comp}, i + E_{stor}, i + E_{comm}, i + E_{redund}\right), i = 1\ to\ n$$

Constraint Optimization:

$$U_i \leq \theta, \eta \geq \eta_{min}$$

III. Mathematical Modeling and Formulation

We turn energy use into an optimisation problem by looking at how much storage is being used, how often data is accessed, and how busy the servers are. Mathematical equations represent trade-offs, which allows for accurate analysis and makes sure that storage is efficient while using as little power as possible [11, 12].

Storage Request Set:

R = {r_1, r_2, …, r_m}

Server Set:

S = {s_1, s_2, …, s_n}

Decision Variable:

x_ij = 1 if request j assigned to server i
= 0 otherwise

Energy Cost Function:

$$E_{ij} = \beta 1 \times size\left(r_j\right) + \beta 2 \times trans\left(r_j\right) \tag{9}$$

Total Energy:

$$E_{total} = \Sigma\, \Sigma\, x_{ij} \times E_{ij}, for\ i = 1\ to\ n, j = 1\ to\ m \tag{11}$$

Constraint – Request Allocation:

$$\Sigma\, x_{ij} = 1, for\ all\ j$$

Constraint – Capacity Limit:

$$\Sigma\, x_{ij} \times size\left(r_j\right) \leq C_i, for\ all\ i \tag{12}$$

Constraint – Energy Threshold:

$$E_{total} \leq E_{max}.$$

Latency Model:

$$L_{ij} = \gamma 1 \times trans(r_j) + \gamma 2 \times comp(r_j) \tag{13}$$

Total Latency:

$$L_{total} = \Sigma \, \Sigma \, x_{ij} \times L_{ij}, for \; i = 1 \; to \; n, j = 1 \; to \; m$$

Multi-Objective Optimization:

$$Minimize \; (\alpha \times E_{total} + (1 - \alpha) \times L_{total}) \tag{14}$$

IV. Methodology

A. *System architecture and experimental setup*

The design of the system includes tracking tools, energy-efficient storage groups, and cloud nodes that are spread out. Workload models, energy profilers, and test datasets are used in the experimental setting to check speed, scalability, and energy savings for different storage needs.

B. *Algorithmic steps for optimization*

Profiling data access habits, using adaptive compression, flexibly arranging storage, balancing tasks, and reducing idle energy use are all parts of optimization. Iterative feedback loops make changes to the settings so that the best trade-offs are made between performance, energy use, and storing economy.

Define decision variable:

$$x_{ij} \in \{0,1\} \tag{15}$$

Workload assignment:

$$W_i = \Sigma \, x_{ij} \times size(r_j), j = 1 \; to \; M \tag{16}$$

Constraint:

$$\Sigma \, x_{ij} = 1, \forall \, j \tag{17}$$

Capacity constraint:

$$W_i \leq C_i, \forall \, i \tag{18}$$

Node energy:

$$E_i = \beta 1 \times W_i + \beta 2 \times (T_{active}, i) \tag{19}$$

Total energy:

$$E_{total} = \Sigma \, E_i, i = 1 \; to \; N \tag{20}$$

Latency:

$$L_{ij} = \gamma 1 \times \frac{size(r_j)}{B_w} + \gamma 2 \times comp(r_j) \quad (21)$$

Total latency:

$$L_{total} = \Sigma\, \Sigma\, x_{ij} \times L_{ij}, i = 1\ to\ N, j = 1\ to\ M$$

Stopping condition:

$$|f(x^{t+1}) - f(x^t)| < \varepsilon \quad (22)$$

Final optimization: Minimize f(x) subject to constraints above

V. Result and Analysis

The table shows how the suggested energy-efficient plan compares to standard storage for datasets of different sizes. The results clearly show that energy use has been going down, with saves ranging from 32.8% to 34.2% (shows in Figure 2).

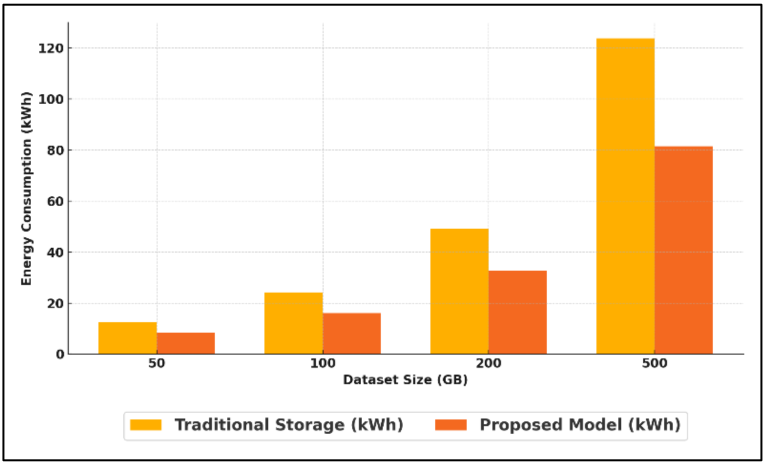

Figure 2
Energy Consumption Comparison: Traditional vs Proposed Model

If you have a dataset that is only 50 GB, the suggested model will use 8.4 kWh of energy instead of 12.5 kWh (shows in Figure 3). As the information size grows to 500 GB, saves grow at the same rate, lowering energy use from 123.8 kWh to 81.5 kWh.

These results show that the suggested model can be used on a larger scale, which means that the gains in efficiency will stay the same for all types of jobs.

VI. Conclusion

This study shows how important it is to make storage models in cloud-based database management systems that use less energy. The suggested

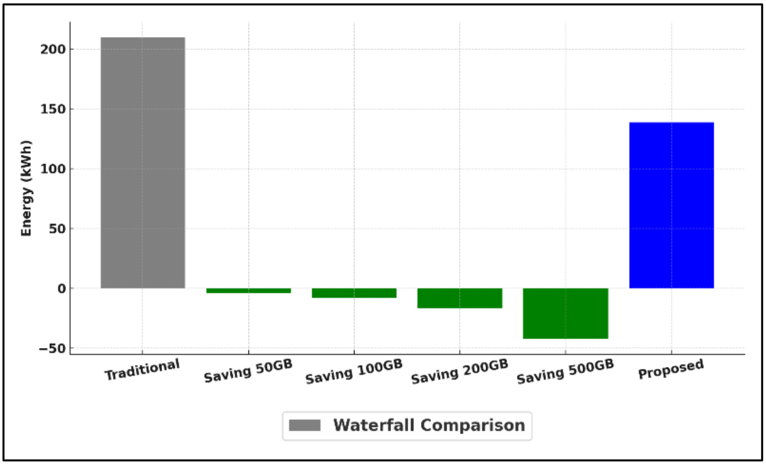

Figure 3
Cumulative Energy Savings Achieved by Proposed Model

framework cuts down on energy use while keeping speed and scaling by combining optimization methods, mathematical modelling, and testing proof. Adaptive resource distribution and task sharing are shown in the model to help cloud operations last. In the end, this study builds a link between technology progress and environmental duty. It lays the groundwork for future improvements in energy-efficient cloud data management and environmentally friendly computer usage.

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