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TOWARDS HYBRID CLOUD INFRASTRUCTURE QUALITY ASSESSMENT MODEL

The paper presents a hybrid model for the cloud infrastructure quality assessment, which combines subjective expert assessments with objective results of statistical analysis. The proposed model, called Hybrid Expert-derived with Entropy-based Weighted Sum Model (HEE-WSM), combines the Analytic Hierarchy Process (AHP) to determine weights based on expert assessments and the entropy-based approach to calculate weights using real data. The proposed HEE-WSM model is a novel approach that takes into account both expert judgments and cloud environment monitoring data. Eight criteria (such as availability, reliability, latency, scalability, performance efficiency, cost, security compliance, and support responsiveness) based on the international standards NIST SP 800-145 and ISO/IEC 25010 are proposed for the cloud infrastructure quality assessment. These criteria are divided into “benefit” and “cost” criteria, which is necessary to ensure normalization and proper comparison of different quality metrics. A hybrid mechanism for determining weighting coefficients allows balancing the weighting coefficients determined on the basis of AHP and the entropy approach using an adjustable coefficient that provides flexibility depending on decision-making needs. Thus, the flexibility of the proposed model is ensured by the ability to adjust the influence of subjective and objective weights of criteria. The final quality assessment is performed using the Weighted Sum Model that aggregates normalized quality metric scores for each alternative. To demonstrate the robustness of the proposed approach, ten leading cloud providers were analyzed in this study, including Amazon Web Services (AWS), Microsoft Azure, Google Cloud Platform (GCP), Alibaba Cloud, and several others. The obtained results demonstrated that the proposed model allows for effective evaluation of cloud services, with GCP receiving the highest total quality score. The proposed approach can be considered an adaptive, transparent, and useful tool for implementation in decision support systems for cloud infrastructure management. The proposed model can be applied in organizations and enterprises for the informed selection of cloud service providers. Future research includes the integration of real-time data monitoring and the application of machine learning methods for automatic adjustment of quality criteria weights.

Keywords: cloud infrastructure quality assessment, expert judgment, entropy-based assessment, hybrid assessment model, quality criteria, cloud service quality metrics, decision making.

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ПРО ГІБРИДНУ МОДЕЛЬ ОЦІНЮВАННЯ ЯКОСТІ ХМАРНОЇ ІНФРАСТРУКТУРИ

У статті представлено гібридну модель оцінювання якості хмарної інфраструктури, яка поєднує суб’єктивні експертні оцінки з об’єктивними результатами статистичного аналізу. Запропонована модель, яка отримала назву Hybrid Expert-derived with Entropy-based Weighted Sum Model (HEE-WSM), поєднує метод аналізу ієрархій (МАІ) для визначення ваг на основі оцінок експертів та ентропійний підхід для розрахунку ваг на основі реальних даних. Запропонована модель HEE-WSM є новим підходом, який враховує як судження експертів, так і дані моніторингу хмарного середовища. Для оцінювання якості хмарної інфраструктури пропонується використовувати вісім критеріїв (таких, як доступність, надійність, затримка, масштабованість, ефективність роботи, вартість, відповідність вимогам безпеки та оперативність підтримки), заснованих на міжнародних стандартах NIST SP 800-145 та ISO/IEC 25010. За типами дані критерії поділяються на «виграшні» та «витратні» критерії, що необхідно для забезпечення нормалізації та належного порівняння різних метрик якості. Гібридний механізм визначення вагових коефіцієнтів дозволяє збалансувати вагові коефіцієнти, визначені на основі МАІ та ентропійного підходу, за допомогою регульованого коефіцієнта, який забезпечує гнучкість залежно від потреб у прийнятті рішень. Таким чином, гнучкість запропонованої моделі забезпечується можливістю регулювати вплив суб’єктивних та об’єктивних ваг критеріїв. Остаточне оцінювання якості проводиться за допомогою моделі зваженої суми, яка агрегує нормалізовані показники метрик якості для кожної альтернативи. Для демонстрації працездатності запропонованого підходу, в роботі було проаналізовано десять провідних хмарних провайдерів, включаючи Amazon Web Services (AWS), Microsoft Azure, Google Cloud Platform (GCP), Alibaba Cloud та деякі інші. Отримані результати продемонстрували, що запропонована модель дозволяє ефективно оцінювати хмарні сервіси, причому GCP отримав найвищу інтегровану оцінку. Запропонований підхід можна вважати адаптивним, прозорим і корисним інструментом для впровадження в системи підтримки прийняття рішень для управління хмарною інфраструктурою. Запропонована модель може бути застосована в організаціях і підприємствах для обгрунтованого вибору постачальників хмарних послуг. Майбутні дослідження включають інтеграцію моніторингу даних у реальному часі та застосування методів машинного навчання для автоматичного коригування ваг критеріїв якості.

Ключові слова: оцінювання якості хмарної інфраструктури, експертне оцінювання, оцінювання на основі ентропії, гібридна модель оцінювання, критерії якості, метрики якості хмарних послуг, прийняття рішень.

Introduction. Cloud computing plays a key role in modern information systems. It provides flexibility, scalability, and reduced IT infrastructure costs. However, assessing the quality of cloud infrastructure remains a challenging task. Cloud services are provided by various vendors. Each of them offers different levels of availability, performance, security, and support. Therefore, it is important to have a formalized quality assessment model. Such a model should take into account several criteria and their relative weights.

One popular approach is the Weighted Sum Model (WSM). It allows different quality indicators to be combined into a single integrated index. This approach has been used in a number of studies in recent years. For example, Basu et al. proposed the use of a fuzzy weighted sum for selecting a cloud service provider based on Service Level Agreements (SLA) [1]. Xiao et al. applied a similar model to balance tasks between data centers and edge nodes. They combined latency and energy consumption as weighting criteria [2]. García-Ayllón et al. evaluated infrastructure based on geospatial data processed in a cloud environment [3].

Thus, the problem of assessing the quality of cloud infrastructure is relevant. It requires a systematic approach that takes into account the multi-criteria nature and diversity of technical indicators.

Related work. Assessing the quality of cloud services requires the use of Multi-Criteria Decision-Making (MCDM) methods. Such methods allow for the consideration of several parameters that influence the choice of a cloud service provider.

The paper of Hosseinzadeh et al. [4] presents a comparative analysis of MCDM methods such as WSM, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [5], and Analytic Hierarchy Process (AHP) [6]. The authors proposed the Weighted Aggregated Sum Product Assessment (WASPAS) method, which is well suited for dynamic cloud environments due to its flexible combination of weighted sums and products.

Mostafa in [7] developed the Best-Only Method (BOM) within the framework of MCDM. This method allows to focus only on the most significant criteria, which reduces the influence of secondary indicators and increases the accuracy of the selection.

The study of Nadeem [8] presents a hierarchical MCDM model that takes into account 15 qualitative factors. The proposed model forms a unified ranking system for Infrastructure as a Service (IaaS) providers based on service quality and usability indicators.

Another approach is presented in the paper of Gireesha et al. [9], where intuitive fuzzy logic was combined with the WASPAS method to provide the Interval-Valued Intuitionistic Fuzzy Sets-Weighted Aggregate Sum and Product Assessment (IIVIFS-WASPAS) method. This approach improves the quality of cloud provider ranking, especially in conditions of data uncertainty.

Tomar et al. [10] proposed a hybrid model that combines objective weights (e.g., through entropy) with subjective expert assessments. This allows the system to be adapted to specific user requirements.

In the work of Saha et al. [11], the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method was used together with the entropy approach to calculate weight coefficients. The model allows determining the relationships between criteria and ranking cloud service providers based on a comprehensive assessment.

All of the above studies demonstrate the importance of combining different decision-making methods for accurate and flexible assessment of cloud infrastructure quality.

Research objective. This paper aims to contribute to the cloud infrastructure quality measurement field by using the introduced Hybrid Expert-derived with Entropy-based Weighted Sum Model (HEE-WSM), which can be applied to assess and improve the quality of cloud infrastructure.

Materials and methods. Cloud infrastructure quality assessment is a complex task that requires consideration of numerous technical and non-technical indicators. Most existing models use either subjective expert methods (e.g., AHP) or objective mathematical approaches (e.g., entropy, TOPSIS).

However, in a real environment, cloud services have both technical measurable characteristics (e.g., latency, availability) and values that depend on the specific user (e.g., security or cost priority). Therefore, it is important to create a model that combines both subjective and objective approaches.

In addition, the technical characteristics of cloud infrastructure can change in real time. For example, latency, throughput, and availability vary depending on the load. Therefore, the quality assessment model must be adaptive to changes in data and usage context. Traditional static ranking models do not take this dynamic into account.

The novel hybrid model should assume the current state of the cloud infrastructure as well as user preferences to be taken into account, enabling a more accurate and flexible assessment of the cloud services quality.

Moreover, the novel quality assessment model must be transparent and easily implementable in real-world Decision Support Systems (DSS). The considered WSM is interpretable and computationally simple, being suitable for integration into IT infrastructure management systems. Thus, the deeper analytical capability could be achieved by combining the WSM with a flexible weighting mechanism based on AHP and entropy calculations.

The cloud infrastructure quality assessment is based on internationally recognized standards, including NIST SP 800-145 (National Institute of Standards and Technology) [12] and ISO/IEC 25010 – a model for software and system quality [13].

These standards define a set of key characteristics that are given in Table 1. In the cloud computing context, these attributes are expanded by technical metrics (i.e., latency, throughput, and SLA compliance).

Table 1 – Cloud infrastructure quality criteria

Criterion	Acronym	Measurement unit	Description
Availability	C1	% uptime	Percentage of time the service is operational
Reliability	C2	hours	Mean Time Between Failure (MTBF)
Latency	C3	milliseconds	Response time for service requests
Scalability	C4	instances / minute	Ability to dynamically scale resources
Performance Efficiency	C5	requests / second	Number of successful requests per second (throughput)
Cost	C6	USD/hour	Pricing per resource unit (CPU, storage, etc.)
Security Compliance	C7	0-1	Compliance with standards (ISO 27001, HIPAA, etc.)
Support Responsiveness	C8	hours	Time taken to resolve support tickets

The proposed cloud infrastructure quality assessment model uses a hybrid weighting mechanism that combines subjective and objective approaches. This approach allows the accurate reflection of both user priorities and actual technical indicators of the cloud environment.

The model uses AHP for subjective weighting, where experts perform pairwise comparisons between criteria C1-C8, as it is demonstrated in Fig. 1. This allows the relative importance of each criterion to be identified in a specific context (e.g., critical applications, government services, business analytics, etc.).

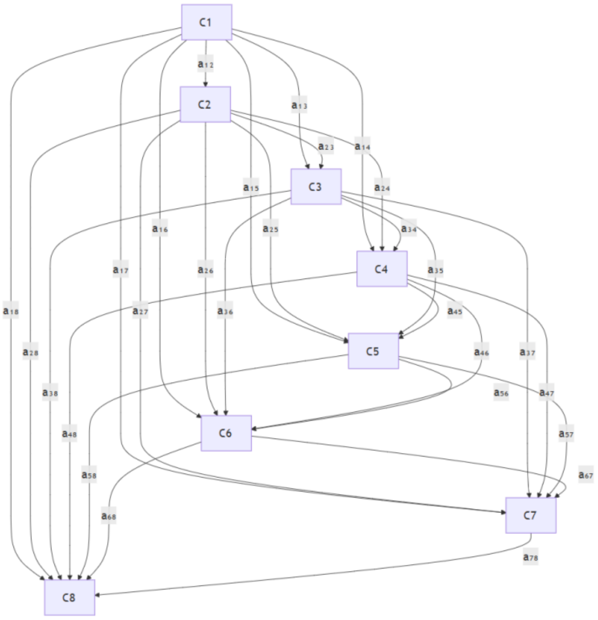

Fig. 1. Pairwise comparisons process between criteria C1-C8

The AHP proposed by Saaty [14] is well known and widely used in MCDM problems to determine priorities among alternatives based on pairwise comparisons.

At the same time, objective weights are calculated based on the entropy method, which analyzes the degree of variability (uncertainty) of criteria C1-C8 values in real measurements. The greater the dispersion in the values of a particular criterion, the higher its informational value and, accordingly, its weight. This objective approach is based on relevant cloud environment monitoring data (e.g., latency, uptime, number of failures).

The entropy method [15] is based on the assumption that the informational value of a criterion depends on the diversity (variability) of its values among alternatives. If the value of the criterion is the same for all objects, it has no discriminatory power and therefore has a low weight. If there is strong variability, the criterion has high informativeness and, accordingly, greater weight in the overall assessment.

Let us assume:

- m is the number of alternatives (e.g., cloud providers);
- n is the number of criteria;
- x_{ij} is the value of criterion j for alternative i.

The values of criteria should be normalized:

- for benefit-type criteria:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}; \quad (1)$$

- for cost-type criteria:

$$p_{ij} = \frac{1/x_{ij}}{\sum_{i=1}^{m} (1/x_{ij})}. \quad (2)$$

During the cloud infrastructure quality assessment, a set of different criteria is applied, which are conditionally divided into two types: benefits and costs (Fig. 2).

Benefit criteria, such as availability (C1), reliability (C2), scalability (C4), throughput (C5), and security compliance (C7), reflect positive characteristics that should be as high as possible. The higher their values, the better the quality of service.

On the other hand, cost criteria, such as latency (C3), cost (C6), and support responsiveness (C8), are undesirable parameters, where lower values are better.

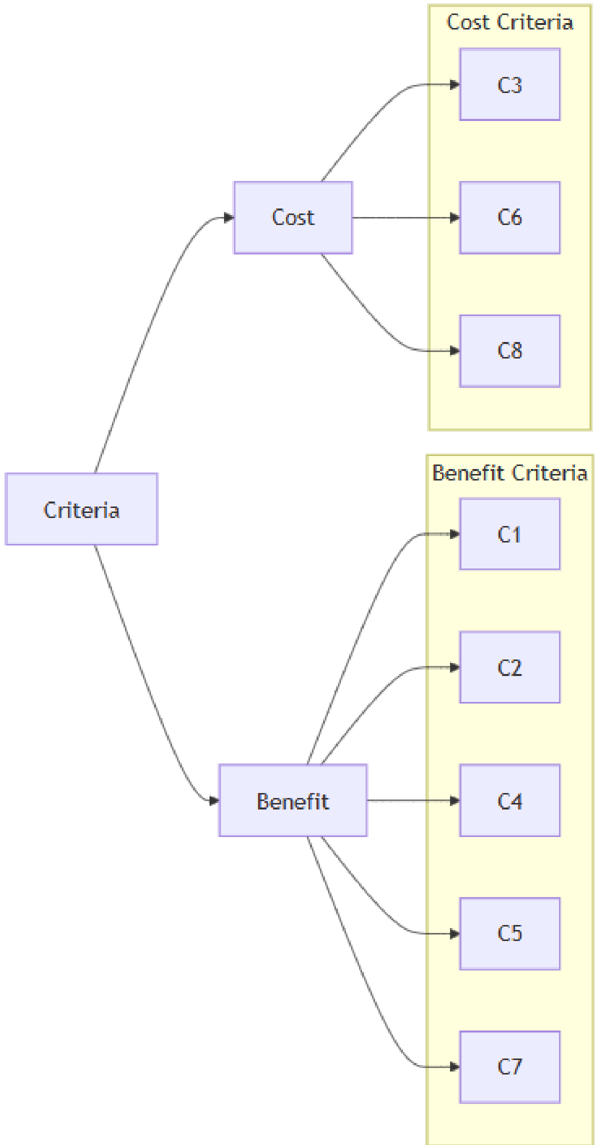

Fig. 2. Used criteria taxonomy

This differentiation of considered criteria is important for the correct data normalization, since multi-criteria analysis methods have different formulas for each type of criterion.

For each criterion the entropy is calculated:

$$e_j = -k \sum_{i=1}^{m} p_{ij} \cdot \ln(p_{ij}), k = \frac{1}{\ln(m)}. \quad (3)$$

If $p_{ij} = 0$, let us assume $p_{ij} \cdot \ln(p_{ij}) = 0$.

The degree of divergence (informativeness) is defined for each criterion:

$$d_j = 1 - e_j. \quad (4)$$

The lower the entropy e_j, the higher the dispersion of values x_{ij}, and therefore, the greater the significance of the criterion.

Therefore, weights are an objective assessment of the importance of each criterion based on actual changes in cloud environment monitoring data:

$$w_j^{entropy} = \frac{d_j}{\sum_{j=1}^{n} d_j}. \quad (5)$$

The final weight of each criterion is calculated as a combination of two components – AHP weight and entropy weight – taking into account the adjustable coefficient α, which allows balancing the influence of subjective and objective parts:

$$w_j = \alpha \cdot w_j^{AHP} + (1 - \alpha) \cdot w_j^{entropy}. \quad (6)$$

The value $\alpha = 1$ corresponds to a completely expert-based approach, while $\alpha = 0$ corresponds only to data from monitoring systems, $0 \le \alpha \le 1$. This ensures the model's adaptability to different usage scenarios.

This hybrid approach not only improves assessment accuracy, but also allows users to interactively change the assessment structure according to requirements or context (e.g., choosing a provider for critical services or for backup data storage).

Finally, the quality metrics are normalized based on:

- for benefit-type criteria:

$$q_{ij} = \frac{x_{ij} - \min\limits_{i=\overline{1,m}} x_{ij}}{\max\limits_{i=\overline{1,m}} x_{ij} - \min\limits_{i=\overline{1,m}} x_{ij}}; \quad (7)$$

- for cost-type criteria:

$$q_{ij} = \frac{\max\limits_{i=\overline{1,m}} x_{ij} - x_{ij}}{\max\limits_{i=\overline{1,m}} x_{ij} - \min\limits_{i=\overline{1,m}} x_{ij}}. \quad (8)$$

The aggregated estimates of alternatives are defined using WSM:

$$Q_i = \sum_{j=1}^{n} w_j \cdot q_{ij}. \quad (9)$$

The alternatives (e.g., cloud providers, services, etc.) then ranked based on the total score Q_i, $i = \overline{1,m}$.

Moreover, the obtained weighted quality metrics of each alternative can be visualized using radar charts for multidimensional analysis.

The proposed approach to assessing the quality of cloud infrastructure combines expert assessments and monitoring data to create a balanced and flexible decision-making model (Fig. 3). The first stage involves selecting alternatives (e.g., cloud providers) and collecting values for eight key quality criteria (C1-C8) based on NIST and ISO/IEC 25010 standards. Next, the criteria are weighted in parallel using two methods: expert and statistical. In the first scenario, the AHP method is used, where experts conduct pairwise comparisons of criteria and form a hierarchy of weights. In the second scenario, weights are calculated based on the entropy method, which takes into account the variability of data for each criterion.

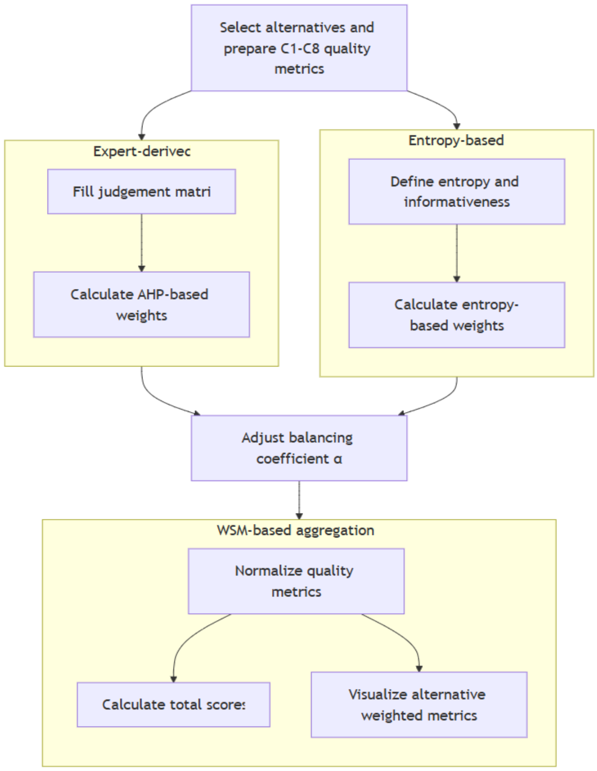

Fig. 3. Proposed approach

Both types of weights are combined using an adjustable balance coefficient α, which allows the model to be adapted to a specific context: the user can prioritize expert opinion or actual measurements. After calculating the combined weights, all criteria are normalized to align them on a scale. Then, the WSM is applied to calculate the total integral score for each alternative. At the final stage, the results are visualized, which makes it easy to compare alternatives and choose the best option.

Results and discussion. Using the proposed model, ten leading cloud service providers representing the main segments of the global market were analyzed.

These include Amazon Web Services (AWS) [16], Microsoft Azure [17], Google Cloud Platform (GCP) [18], IBM Cloud [19], Oracle Cloud Infrastructure [20], DigitalOcean [21], Alibaba Cloud [22], Linode [23], Vultr [24], and Hetzner Online [25].

These cloud providers were selected based on their widespread use, diversity of architectural solutions, and availability of open information on key quality indicators. Thus, the analysis covers both global (e.g., AWS, Azure, GCP) and mid-range providers with regional or specialized coverage (e.g., Linode, Hetzner, DigitalOcean), providing a complete picture of the cloud services market.

Tables 2 and 3 illustrate the different types of criteria used to assess the quality of cloud infrastructure. Table 2 contains benefit-type criteria, the values of which should be as high as possible to achieve a better rating (C1, C2, C4, C5, and C7).

Table 2 – Benefit criteria values of cloud providers

Provider	C1	C2	C4	C5	C7
AWS	99.99	6000	25	3000	0.95
Microsoft Azure	99.95	5800	22	2800	0.93
Google Cloud	99.99	6200	28	3200	0.94
IBM Cloud	99.9	5500	15	2200	0.9
Oracle Cloud	99.92	5700	20	2500	0.88
DigitalOcean	99.85	5000	12	1800	0.75
Alibaba Cloud	99.94	5900	23	2900	0.9
Linode	99.8	4800	10	1700	0.7
Vultr	99.83	4900	11	1750	0.68
Hetzner	99.88	5200	14	1900	0.72

Table 3 denotes cost-type criteria (C3, C6, and C8), where lower values indicate higher service quality.

Table 3 – Cost criteria values of cloud providers

Provider	C3	C6	C8
AWS	95	0.6	1
Microsoft Azure	100	0.58	1.5
Google Cloud	90	0.62	1
IBM Cloud	110	0.65	2
Oracle Cloud	105	0.55	2.5
DigitalOcean	120	0.4	3
Alibaba Cloud	102	0.53	1.8
Linode	130	0.38	4
Vultr	125	0.35	4.2
Hetzner	115	0.3	3.5

These numbers (Table 2 and 3) are based on typical ranges reported in industry benchmarks and public SLAs for the given providers [16–25].

The sample pairwise comparisons between criteria C1-C8 (Table 4) shows the relative importance ratings of each pair of criteria according to the AHP [4], where the values reflect the one criterion's preference over another.

Table 4 – Pairwise comparisons between criteria C1-C8

Criteria	C1	C2	C3	C4	C5	C6	C7	C8
C1	1	1	3	3	5	4	2	6
C2	1	1	3	3	5	4	2	6
C3	1/3	1/3	1	2	3	2	1	3
C4	1/3	1/3	1/2	1	2	2	1	2
C5	1/5	1/5	1/3	1/2	1	2	1	2
C6	1/4	1/4	1/2	1/2	1/2	1	1	2
C7	1/2	1/2	1	1	1	1	1	2
C8	1/6	1/6	1/3	1/2	1/2	1/2	1/2	1

Hence, the maximum eigenvalue is $\lambda_{max} = 8.33$ and the consistency index is:

$$CI = \frac{\lambda_{max} - m}{m-1} = \frac{8.33-8}{8-1} = 0.05. \quad (10)$$

Having the random index for $m = 8$ is equal to $RI = 1.41$, the consistency rate is:

$$CR = \frac{CI}{RI} = \frac{0.05}{1.41} = 0.03 < 0.1. \quad (11)$$

Since obtained CR value is less than 10%, the given in Table 4 pairwise comparisons between criteria C1-C8 can be considered to be consistent.

Table 5 shows the weights of criteria C1–C8 obtained using the AHP method (expert assessment) and the entropy approach (objective assessment based on data), as well as balanced weights calculated using the coefficient $\alpha = 0.5$, which ensures an equal contribution of both approaches.

Table 5 – Weights of criteria C1-C8

Criteria	AHP-based	Entropy-based	Balanced
C1	0.26	0.15	0.20
C2	0.26	0.14	0.20
C3	0.12	0.14	0.13
C4	0.09	0.11	0.10
C5	0.07	0.13	0.10
C6	0.06	0.12	0.09
C7	0.09	0.14	0.12
C8	0.04	0.06	0.05

Fig. 4 shows how balanced weights of criteria C1-C8 change when the coefficient α is changed from 0 to 1.

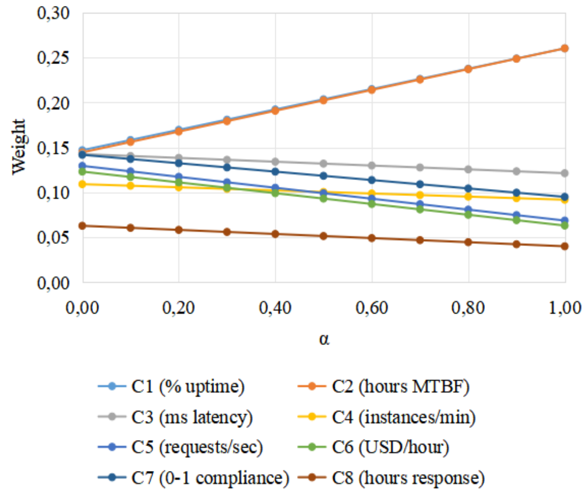

Fig. 4. Balanced weights of criteria with different α

Table 6 demonstrates normalized benefit-type criteria values obtained using (7) based on the original values from SLAs and benchmarks given in Table 3.

Table 6 – Normalized benefit-type criteria values

Provider	C1	C2	C4	C5	C7
AWS	1.00	0.86	0.83	0.87	1.00
Microsoft Azure	0.79	0.71	0.67	0.73	0.93
Google Cloud	1.00	1.00	1.00	1.00	0.96
IBM Cloud	0.53	0.50	0.28	0.33	0.81
Oracle Cloud	0.63	0.64	0.56	0.53	0.74
DigitalOcean	0.26	0.14	0.11	0.07	0.26
Alibaba Cloud	0.74	0.79	0.72	0.80	0.81
Linode	0.00	0.00	0.00	0.00	0.07
Vultr	0.16	0.07	0.06	0.03	0.00
Hetzner	0.42	0.29	0.22	0.13	0.15

Table 7 outlines normalized cost-type criteria values obtained using (8) based on the original values from SLAs and benchmarks given in Table 4.

Table 7 – Normalized cost-type criteria values

Provider	C3	C6	C8
AWS	0.88	0.14	1.00
Microsoft Azure	0.75	0.20	0.84
Google Cloud	1.00	0.09	1.00
IBM Cloud	0.50	0.00	0.69
Oracle Cloud	0.63	0.29	0.53
DigitalOcean	0.25	0.71	0.38
Alibaba Cloud	0.70	0.34	0.75
Linode	0.00	0.77	0.06
Vultr	0.13	0.86	0.00
Hetzner	0.38	1.00	0.22

For example, the aggregated estimate for $i = 1$ (i.e. AWS provider) is calculated using WSM (9) as follows:

$$Q_1 = \sum_{j=1}^{n} w_j \cdot q_{1j} = \\ = 0.20 \cdot 1.00 + 0.20 \cdot 0.86 + 0.13 \cdot 0.88 + \\ +0.10 \cdot 0.83 + 0.10 \cdot 0.87 + 0.09 \cdot 0.14 + \\ +0.12 \cdot 1.00 + 0.05 \cdot 1.00 = 0.84. \quad (12)$$

Another aggregated estimate, i.e. for $i = 2$ (i.e. Azure provider) is calculated using WSM (9) as follows:

$$Q_2 = \sum_{j=1}^{n} w_j \cdot q_{2j} = \\ = 0.20 \cdot 0.79 + 0.20 \cdot 0.71 + 0.13 \cdot 0.75 + \\ +0.10 \cdot 0.67 + 0.10 \cdot 0.73 + 0.09 \cdot 0.20 + \\ +0.12 \cdot 0.93 + 0.05 \cdot 0.84 = 0.72. \quad (13)$$

Table 8 demonstrates weighted normalized values of benefit-type criteria (Table 6).

Table 8 – Weighted normalized benefit-type criteria values

Provider	C1	C2	C4	C5	C7
AWS	0.20	0.17	0.08	0.09	0.12
Microsoft Azure	0.16	0.14	0.07	0.07	0.11
Google Cloud	0.20	0.20	0.10	0.10	0.11
IBM Cloud	0.11	0.10	0.03	0.03	0.10
Oracle Cloud	0.13	0.13	0.06	0.05	0.09
DigitalOcean	0.05	0.03	0.01	0.01	0.03
Alibaba Cloud	0.15	0.16	0.07	0.08	0.10
Linode	0.00	0.00	0.00	0.00	0.01
Vultr	0.03	0.01	0.01	0.00	0.00
Hetzner	0.09	0.06	0.02	0.01	0.02

Table 9 demonstrates weighted normalized values of cost-type criteria (Table 7).

Table 9 – Weighted normalized cost-type criteria values

Provider	C3	C6	C8
AWS	0.12	0.01	0.05
Microsoft Azure	0.10	0.02	0.04
Google Cloud	0.13	0.01	0.05
IBM Cloud	0.07	0.00	0.04
Oracle Cloud	0.08	0.03	0.03
DigitalOcean	0.03	0.07	0.02
Alibaba Cloud	0.09	0.03	0.04
Linode	0.00	0.07	0.00
Vultr	0.02	0.08	0.00
Hetzner	0.05	0.09	0.01

Fig. 5 shows the examples of the obtained total scores for each of the ten cloud providers, calculated using the WSM with balanced criteria weights, where the balance coefficient is $\alpha = 0.5$.

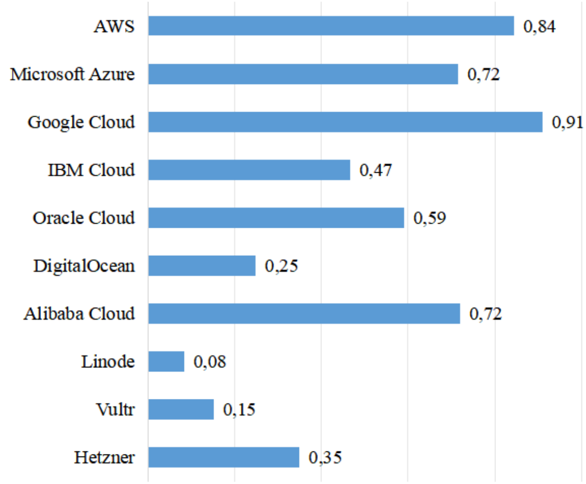

Fig. 5. Total quality assessment scores for $\alpha = 0.5$

The outlined example calculation takes into account expert assessments and objective weights obtained using the entropy analysis.

As can be seen from Fig. 5, GCP received the highest score (0.91), indicating its superiority in most key quality criteria. Next are AWS (0.84), Microsoft Azure (0.72), and Alibaba Cloud (0.72) which also have high scores.

In contrast, DigitalOcean (0.25), Linode (0.08), and Vultr (0.15) received the lowest scores, indicating limited compliance with the considered criteria.

Fig. 6 demonstrates domination of GCP and AWS on the radar chart.

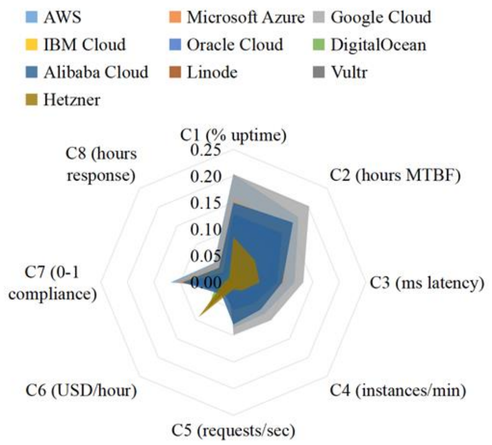

Fig. 6 – Domination of GCP and AWS for $\alpha = 0.5$

Such a visual comparison of assessed cloud providers can be further developed to create interactive analytical dashboards to support intelligent decision-making. This can be achieved by introducing "what if" analysis and AI-driven conversational suggestions and insights.

Conclusion and future work. This study proposed a Hybrid Expert-derived with Entropy-based Weighted Sum Model (HEE-WSM) for the cloud infrastructure quality assessment, which combines the WSM with a dual criterion weighting approach. This approach takes into account both subjective expert assessments (AHP-based) and objective statistical data (entropy-based), which allows achieving a balance between user judgment and technical indicators. The model uses eight quality criteria C1-C8 based on NIST and ISO/IEC 25010 standards, covering key parameters of cloud services, including availability, latency, scalability, cost, security, and others. The results of 10 leading cloud providers analysis show the robustness of the proposed approach for decision-making in the cloud environment.

In the future, the model should be extended by adding real-time monitoring and using machine learning methods to adjust weights based on load type and context

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