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AI-Assisted Characterization of Cooling Patterns in a Water-Cooled ICT Room

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Abstract

Information Communication Technology (ICT) centers play a vital role as essential facilities within our digitalized society. Energy efficiency holds great significance in the ICT sector, driven by the rising energy costs and to reduce the environmental impact. Simultaneously, it is essential to ensure a sufficient cooling supply for servers. Artificial Intelligence (AI) can be used to analyze patterns in large datasets, facilitating valuable insights that are difficult for humans to analyze alone because of the complexity and size of the datasets. The aim of this research is to characterize cooling patterns and explore how AI-driven clustering algorithms can be used to identify cooling operational statuses. The research object is an ICT room situated in Linköping, Sweden, and operated by the global telecommunications company Ericsson AB. The ICT room has Liquid Cooling Packages (LCPs) for water-based cooling.

The results show that the average cooling power density in the ICT room is 6.98 kW/m\textsuperscript{2}, and the interquartile range is 8.26 kW/m\textsuperscript{2}. The results also demonstrate the potentialities in using AI-based clustering algorithms, K-means in the presented research, to uncover insights related to cooling operational statuses. Furthermore, the results show that it is suitable to divide the data points into four clusters, providing a detailed description of the characteristics of the dataset. The identified clusters differ with regards to variables, among other, such as LCP return air temperature and temperature difference between chilled water supply and return. This is beneficial in identifying undesired operational statuses of LCPs, e.g., low temperature difference between chilled water supply and return, which is an indicator of a poor cooling performance.

Keywords—ICT Center, AI, Cooling patterns, Water-cooling, K-means clustering

I. INTRODUCTION

Information Communication Technology (ICT) centers are crucial infrastructure in our society for data processing, storage of large amounts of data and information, as well as communications. The importance of ICT centers will most likely be magnified in future with the ongoing digitalization in various sectors. Moreover, the European Commission's digital compass highlights the pivotal role of digitalization in achieving global sustainability goals [1]. A critical issue in ICT centers is increasing operating costs due to a high energy use for operation of servers and cooling. Improving cooling processes in this sector holds substantial potential for energy efficiency, according to the EU Code of Conduct on Data Centre Energy Efficiency [2]. Additionally, adequate cooling supply is essential in maintaining suitable operating temperatures in servers, as well as to ensure server performance. However, it is important to be aware of that excessive cooling supply increases energy use and operational costs. By ensuring a suitable cooling strategy it is possible to decrease energy use and increase the lifespan of servers. Artificial Intelligence (AI) algorithms enable the analysis and monitoring of energy use in large datasets, making it possible to identify potential energy efficiency improvements in ICT centers. Furthermore, AI-based clustering algorithms can be used to identify patterns in large datasets [3], which is a challenging task for humans to handle alone due to the vast volume of data. From an ICT center perspective, clustering algorithms hold the potential for identification of operational patterns based on sensor data gathered from cooling equipment. This is beneficial for identifying groups of cooling equipment that deviate from desired operational statuses and can be corrected where needed.

Despite the growing body of research on energy efficiency in ICT centres, there is a notable research gap on AI-assisted analysis of cooling performance for servers [4]. The existing research regarding energy efficiency in ICT centers has to a large extent focus on the energy modelling aspects of IT loads and airflow management, such as those presented in [5, 6]. This research aims to characterize cooling power density and investigate how an AI-based clustering algorithm can be used to identify cooling operational patterns and undesired operational statuses. Furthermore, this study provides valuable insights on how clustering algorithms can be used to detect deviating patterns where attention from operators is needed, demonstrated through a real-world example. This sheds light on the potential of using AI-based tools in the decision-making processes related to cooling operations in
ICT centers. The research object is a water-cooled ICT room in Linköping, Sweden, which is operated by the global telecommunications company Ericsson AB.

II. THEORY

A. Cooling techniques in ICT centers

Air cooling is the most common cooling technique in ICT centers, primarily due to its ease of application and operation [7]. Server-racks are in general arranged into hot and cold aisles in these ICT centers [8], and the cold air generated by Computer Room Air Handlers (CRAH) units is directed to cold aisles through the floor, ceiling, or horizontally located CRAH units. The increase in power density within ICT centers has given rise to problems regarding inadequate cooling by CRAH units [8]. Liquid-based cooling techniques, with a higher heat transfer capability compared to air, have emerged as a solution to deal with this issue, as well as to achieve energy savings [9]. The transfer of heat from server equipment in these systems is achieved using either water or dielectric liquid [10]. Liquid cooling-based systems differentiate primarily on how close the liquid is relative to the server equipment. An example includes a combination between air and liquid cooling. This system is based on using a heat exchanger to decrease the return air temperature and simultaneously transfer heat from the air to the liquid. Hence, a better separation between the hot and cold air is allowed.

B. AI-based methods for data clustering

Clustering is an AI-based, unsupervised method of dividing a set of data objects into subsets, i.e., clusters [11]. Data objects within the same cluster have similar characteristics but differ from other clusters. Moreover, in the context of AI, unsupervised learning algorithms, such as clustering, identify patterns without labeled data, whereas supervised learning algorithms are trained using labeled data. The key clustering methods can be divided into partitioning methods, hierarchical methods, density-based methods, and grid-based methods [11]. Partitioning methods are the most fundamental clustering approaches. Moreover, the most commonly used and established partitioning method is K-means. The algorithm operates by selecting K random objects as initial cluster centers and assigns each remaining object to the nearest center based on Euclidean distance, which allows for comparing the similarity between data points. Thereafter, K-means iteratively improves the within-cluster variation by recalculating the mean of each cluster and reassigning the data points until convergence when no data points are assigned to a different cluster. See Fig. 1 for a summary of the K-means clustering approach.

The objective function that K-means aims to minimize is the within-cluster sum of squares (WCSS), see (1). K represents the predetermined number of clusters, p a data point assigned to cluster i, ci is the cluster center of cluster C, corresponding to the estimated mean vector, and the squared Euclidean distance between p and ci is denoted by dist(p, ci).

\[
WCSS = \sum_{i=1}^{k} \sum_{p \in C_i} \text{dist}(p, c_i)^2
\]

III. METHODOLOGY

A. Research process

The research process comprises of three steps, as shown in Fig. 2. Firstly, data for energy use related to the cooling system is collected. Secondly, a suitable algorithm is selected and adopted that allows for data interpretation and analysis of cooling patterns in the studied ICT room, which is the last step of the research process.

B. Data collection

Energy use data for the cooling system was collected from January 1st, 2021, to November 10th, 2021. The dataset consists of over 90,000 data points with a five-minute time interval. Collected parameters include chilled water flow rate (l/min), chilled water supply and return temperature\(^1\) (°C), Liquid Cooling Package (LCP) return air temperature (°C), and cooling power (kW). Fig. 3 visualizes the investigated ICT room, which consists of three rows of servers (Rows 1–3). Each row has seven LCP units (Positions A–G), and the room has an area and volume of 144 m\(^2\) and 504 m\(^3\), respectively. The total server area in the room is 34 m\(^2\).

\(^1\) The temperature difference between chilled water supply and return temperature is hereafter referred to as “\(\Delta T_{\text{chilled water}}\).
C. Selection and adoption of algorithm

In this research, the dataset described above was analysed using K-means in the statistical software tool R [12]. The software is well-established among data scientists and academics for analysis and visualization of data, as well as AI. The selection of K-means is explained by the following features: (1) ease of implementation, (2) effective way to cluster data, (3) ability to handle large sets of data, and (4) effective visualization of the clustered data, enabling users to interpret the results visually. Prior to implementation of the K-means algorithm, the entire dataset was normalized in order to avoid issues from variations in variable units and different magnitudes between the variables. Moreover, the optimal number of clusters was determined using the elbow method in which the "elbow point" is identified, i.e., adding more clusters does significantly decrease the WCSS. It should be noted that disadvantages of the elbow method includes subjectivity in the identification of the "elbow point" and the lack of distinctive "elbow point". In this research, the optimal number of clusters is determined to be four. Analysis also indicates that selecting three clusters may be suitable. The reason for selecting four clusters and not three is motivated by the purpose to capture a more detailed representation of various cooling characteristics within the dataset.

It is important to note that the use of other clustering algorithms has been considered and evaluated in this study. For example, hierarchical clustering and density-based, i.e., Density-Based Spatial Clustering of Applications with Noise (DBSCAN), clustering algorithms were investigated. The hierarchical clustering algorithm was computationally expensive and scaled poorly with larger datasets. The DBSCAN clustering algorithm provided a few large clusters because the data points were not well separated, which was a result of difficulties in adjusting hyperparameters. Consequently, this created difficulties during interpretations of the results.

D. Interpretation and analysis

Followed by the K-means clustering is the data interpretation and analysis. In this step the data categorization is investigated related to variables in the dataset, such as chilled water flow rate (l/min), and \( \Delta T_{\text{chilled water}} \) (°C) of LCPs. This enables differentiation of clusters with regards to cooling performance, and consequently identifying deviating characteristics where attention is needed to reconfigure Proportional Regular Derivatives (PID) parameters. Hence, this analysis allows for the identification of undesired cooling performance and operational behavior.

IV. RESULTS AND ANALYSIS

A. Cooling power density

The cooling power density (kW/m²) for the LCPs during the investigated time period, i.e., January 1st, 2021 to November 10th 2021, can be seen in Fig. 4. The diagrams presented consider the number of server racks and the corresponding area to which each group of LCPs is connected. The average cooling power density in the ICT room is 6.98 kW/m², and the interquartile range is 8.26 kW/m². LCP 3A has the lowest cooling density, i.e., 0.02 kW/m², and LCPs 3D–3E have the highest cooling power density corresponding to 13.48 kW/m². This illuminates large differences in cooling power density between the various LCPs. Furthermore, as shown in Fig. 4, it can be seen that several LCPs, e.g., 1A–1C and 3A, were non-operational during the initial half of the investigated time period. As a result, this decreases the average cooling power density. Additionally, the total cooling power in the ICT room is increased by two thirds from the beginning of the analyzed time period, ~180 kW, to the end of the analyzed time period, ~300 kW. Hence, using solely figures on cooling power from the end of the analyzed time period would increase the average cooling power density in the ICT room to 8.93 kW/m² (28 %).

B. K-means clustering - cooling operational patterns

As stated in section III.C, the optimal number of clusters in this application is determined to be four. The cluster averages for the variables chilled water flow rate (l/min), \( \Delta T_{\text{chilled water}} \) (°C), LCP return air temperature (°C), and cooling power (kW) can be seen in Table 1. The main characteristics of the four clusters can be summarized as follows. Cluster 1 = low LCP return air temperature and low cooling power explained by that the LCPs are non-operating during large parts of the analyzed time period. Cluster 2 = moderate LCP return air temperature, rather low chilled water flow rate, and high \( \Delta T_{\text{chilled water}} \). Cluster 3 = high LCP return air temperature and chilled water flow rate, and rather low \( \Delta T_{\text{chilled water}} \). Cluster 4 = high LCP return air temperature, rather high chilled water flow rate and \( \Delta T_{\text{chilled water}} \). Given that a high temperature difference between the chilled water supply and return, along with a low chilled water flow rate, is important for energy-efficient cooling operation of ICT rooms, these findings are important in identifying undesired operational statuses in various clusters and LCP units, where there is a need to reconfigure PID parameters. For example, Cluster 3 has a high average chilled water flow rate, 35.6 l/min, but a rather low \( \Delta T_{\text{chilled water}} \), 8.8 °C. From an energy-efficient perspective it is preferable to have a higher \( \Delta T_{\text{chilled water}} \) and a lower water flow rate. Another indicator of a poor cooling performance is the moderate average LCP return air temperature in Cluster 2, which is 32.6 °C. This is between 1.4–2.5 °C lower in comparison to Clusters 3 and 4, which may indicate excessive cooling supply to Cluster 2.

The relative frequency distribution of each cluster for all LCPs is visualized in Fig. 5. Differentiating the four clusters across all LCPs enables the analysis of LCPs with suboptimal...
cooling performance, and the identification of what variables are of interest to investigate concerning PID parameters. When analyzing the average LCP return air temperature, as in the example above, it can be seen that, among others, Row 1B, Row 1G, and Row 3B, are important to further investigate from a PID parameter standpoint. This is because these LCPs are characterized by almost exclusively Clusters 1 and 2, i.e., the clusters with the lowest LCP return air temperature. Consequently, the presented research shows that by continuous monitoring and measurement of variables describing cooling performance of LCP units, together with AI-based clustering algorithms, enables identification of what LCPs, and variables, may be suitable for further investigation regarding PID parameters and cooling performance.

**Table 1. Cluster averages for the variables.**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Cluster 1</th>
<th>Cluster 2</th>
<th>Cluster 3</th>
<th>Cluster 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>LCP return air temperature (˚C)</td>
<td>30.9</td>
<td>32.6</td>
<td>35.1</td>
<td>34.0</td>
</tr>
<tr>
<td>Chilled water flow rate (l/min)</td>
<td>0.15</td>
<td>12.8</td>
<td>35.6</td>
<td>22.7</td>
</tr>
<tr>
<td>Cooling power (kW)</td>
<td>0.2</td>
<td>11.3</td>
<td>21.9</td>
<td>17.0</td>
</tr>
<tr>
<td>(\Delta T) chilled water (˚C)</td>
<td>15.3</td>
<td>12.6</td>
<td>8.8</td>
<td>10.7</td>
</tr>
</tbody>
</table>

**Fig. 5. Relative frequency distribution of the clusters for all LCPs.**

Fig. 6–Fig 8 shows scatter plots of the LCP return air temperatures as a function of cooling power, \(\Delta T\) chilled water, and chilled water flow rate, respectively. Analysis of the relationship between these variables can provide a comprehensive understanding of the cooling characteristics for each LCP in the studied ICT room. Additionally, the relationship between the LCP return air temperature and the three other variables gives an indication for identifying which PID parameters need to be further investigated. The key findings for each cluster in Fig. 6–Fig 8 are as follows:

- Cluster 2 has a rather high \(\Delta T\) chilled water and a rather low chilled water flow rate in several LCPs, such as ROWs 1A, 2C, and 3B, which suggests good cooling performance. However, as stated previously in this section, the average LCP return air temperature is considerably lower than in Clusters 3 and 4. Hence, it is of interest to explore if there is potential for decreased cooling supply to Cluster 2, whilst maintaining suitable operating temperatures in the servers.

- Cluster 3 demonstrates the highest LCP return air temperatures, seen in e.g., ROWs 1D, 1E, and 1F. However, the rather low \(\Delta T\) chilled water and high chilled water flow, seen in e.g., ROWs 2D and 2E, suggests that there is a need to reconfigure the PID parameters.

- As for Cluster 3, Cluster 4 has high LCP return air temperatures, which can be seen in e.g., ROWs 1D, 1E, and 1F. However, this particular cluster is characterized by higher \(\Delta T\) chilled water and lower chilled water flow, which is advantageous from an energy efficiency perspective. The cooling characteristics of ROWs 1D, 1E, and 1F are examples of the described observations.

**Fig. 6. Relationship between LCP return air temperature and the cooling power.**

**Fig. 7. Relationship between LCP return air temperature and \(\Delta T\) chilled water.**
The findings of this study demonstrate the potentialities in using the K-means algorithm for grouping data points related to cooling variables of LCP units. Additionally, the results show that it is suitable to divide the data points into four clusters. The identified clusters differ with regards to variables, among other, such as LCP return air temperature and temperature difference between chilled water supply and return. This is beneficial in identifying undesired operational statuses of LCPs, e.g., low temperature difference between chilled water supply and return, which is an indicator of a poor cooling performance. Clusters 1 is characterized by a combination of low LCP return air temperature and low average cooling power, which can be attributed to non-operational periods during large parts of the analyzed time period. Cluster 2 has moderate LCP return air temperature, relatively low chilled water flow rate, and high ∆T_chilled_water. In contrast, Cluster 3 demonstrates high chilled water flow rate and LCP return air temperatures, with relatively low ∆T_chilled_water. Finally, Cluster 4 is featured by high LCP return air temperature, rather high ∆T_chilled_water, and chilled water flow rate. It should be highlighted that in the context of energy efficiency, it is preferable to have a high ∆T_chilled_water, and a low chilled water flow rate, meaning that Cluster 4 is preferred compared to Cluster 3.

With regards to the use of K-means as method in this research, it enhances data visualization and aids in deeper understanding of complex patterns within a dataset. Consequently, K-means can be used as a tool for data-driven analysis of cooling patterns in ICT rooms. Within the context of this research project, the use of K-means has been key for communication of results to facility management consultants and employees at Ericsson AB. Hence, undesired cooling patterns that deviate from the desired ones can be effectively communicated. Moreover, it is important to address the selection of four clusters, instead of three clusters, which were also considered suitable as previously mentioned. The motivation for this is to obtain a more detailed and comprehensive representation of the cooling characteristics in the dataset. As a result, this allows for a more granular depiction of the cooling patterns in the investigated dataset.

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