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Customers Lifetime Value-Based Segmentation using Hybrid K-means Clustering and Analytic Hierarchy Process: a Case Study of an Indonesian National Electricity Company

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| --- | --- | --- |
| **A B S T R A C T S** |  | **A R T I C L E I N F O** |
| To effectively manage the increasing electricity demand, developing predictive analytics based on understanding the customers' electricity consumption patterns is essential. This study presents a hybrid customer segmentation analytics by combining the K-Means clustering, customer lifetime value concept, and analytic hierarchy process. The analytics is useful for decision-making in defining service strategies integrated with customer relationship management. This study uses more than 16 million records of customer electricity consumption data from January 2019 to December 2020. We use K-Means clustering to identify the initial market segments. Next, we evaluate and validate the customer segmentation results using the customer lifetime value concept and analytical hierarchy process. Three customer segments were identified. We propose a continuous replenishment program for the first customer group, less-profitable customers. This type of customer will implement partnership programs to encourage increased electricity consumption and retail account marketing, such as must carry out further customer profiling by providing service product information following customer profiles using CRM in line with the customer ID. While for the second and third customer groups, which are profitable customers, we propose business to business this type of customer will implement increase their energy consumption by offering premium service products without going out during peak usage and customer business development strategy such as by providing special executive accounts to customers to provide the best solutions and consultation on electrical problems.  © 2021 Tim Pengembang Jurnal UPI |  | ***Article History:***  *Received 00 Jun 20xx*  *Revised 00 Jul 20xx*  *Accepted 00 Jul 20xx*  *Available online 00 Sep 20xx*  \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_  ***Keyword:***  *Analytics,*  *Customer Analytics,*  *K-Means Clustering,*  *Electricity,*  *Customer Lifetime Value,*  *Customer Relationship Management,*  *Analytical Hierarchy Process.* |



**1. INTRODUCTION**

The electricity consumption in Indonesia continues to increase from 2015 to 2020 by 98.89%, with business customers dominating electricity consumption (Katadata, 2020). PT. PLN Persero is the only electricity provider in Indonesia providing higher electricity power for the entire region, including the West Sumatra region. While the electricity demand of business customers is increasing, electricity blackouts often occur up to a high frequency of four times a month. Based on the data analysis results that have been carried out, power outages cause the average electricity usage time for business customers to be under 50 hours per month. Based on information from the Commercial Manager of PLN for the West Sumatra Region, the incident was due to customers using power above 200 thousand using a higher peak load electricity usage time than electricity outside peak hours. During off-peak hours, customers rarely use it. Based on these problems, PT. PLN Persero West Sumatra must understand the characteristics of the customer's electricity use so that the use of electricity at times outside the peak load can be allocated resources that are appropriate and on target-to-target customer segmentation.

Customer segmentation is one way to understand and map customer preferences. According to previous research, customer segmentation refers to grouping customers based on similar characteristics (McLoughlin et al., 2015). Thus, customer segmentation can predict future actions in consuming the services. That customers use and build relationships and enhance customer commitment to building a solid business (McLoughlin et al., 2015) ;(Ye, 2021) several previous studies discussed customer segmentation on customers' electricity consumption (Camero et al., 2018) (Gajowniczek & Zabkowski, 2018); (Lee et al., 2020), and electricity demand (Jang et al., 2021) . The research context is more about finding new customer behavior patterns in consuming electricity, and more methods use a combination of K-Means and Self Organizing Maps (SOM) and other clustering methods (Camero et al., 2018) (Gajowniczek & Zabkowski, 2018), (Lee et al., 2020). Other studies use the regression method for customer segmentation (Jang et al., 2021). They want to predict future electricity consumption to meet electricity demand from customers. The results of several previous studies provide recommendations for optimization of the use of electricity to the electricity that has been provided consumption (Camero et al., 2018); (Gajowniczek & Zabkowski, 2018); (Lee et al., 2020). There are also other studies analyzing customer characteristics by applying the K-Means Clustering model by analyzing tariffs, power, the number of bills paid and then from the model results. The concept is used in Customer Relationship Management (CRM) to gain insight or make company business decisions (Afthoni et al., n.d.).

Previous research on customer segmentation commonly was based on total electricity consumption per day consumption (Camero et al., 2018);(Gajowniczek & Zabkowski, 2018), ;(Lee et al., 2020),. Another study only analyzed rates, electricity, and total bills by combining K-Means and CRM (Afthoni et al., n.d.). Therefore, this study fills the gap by analyzes based power, peak load electricity consumption, and peak external load electricity consumption by applying a combination of the K-Means clustering method (Bapna, Goes, Gupta, & Jin, 2004), customer lifetime value concept, and analytic hierarchy process. The method can handle large-sized data such as the one we use, i.e., data from PT. PLN Persero West Sumatra Region from 2019 to 2020. Data features are installed power at the customer, peak load electricity usage time, peak load electricity usage time. The analysis results are useful to improve future marketing strategy decisions. This improvement can help the company to optimize electrical power services.

The first part of this article describes the background of the problem, gaps in the research, the purpose, literature review on customer segmentation carried out in previous studies. Section 3 narrates the research method. Section 4 explains the results and discussion. Section 5 presents the conclusions, implications, current limitations, and future research.

**1.1. Customer Segmentation Based on Electricity Consumption Data**

Table 1 presents previous studies on customer segmentation using transaction/ customer credentials data. We categorize the articles based on their business context, dataset, segmentation features, and the segmentation method.

**Table 1.** Reviewed Studies on Customer Segmentation in Electricity Consumption

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Article | Business Context | Dataset | Segmentation Features | Segmentation Method |
| (McLoughlin et al., 2015) | Electricity Load Profile in Ireland | Experimental data period January 1, 2009, to December 31, 2010, | Dwelling type, No. of bedrooms, Age, Social Class, Electronic Type | K-means, k-medoid and Self Organizing Maps (SOM) |
| (Toussaint & Moodley, 2020) | Electricity Consumption in South Africa | South Africa Electric Load Profile Data from 1994 to 2014 | X=Hour (load profile multiple one days)  Y= X multiple All household | K-Means  And Self Organizing Maps (SOM) |
| (Camero et al., 2018) | Electricity  Demand Signature in Andalusian | The load data of 64 buildings located in Andalusia, Spain | Identity, Industrial Division, Industrial Categories, Mean Power Consumption, Power Consumption | Variable selection (Feature Selection), Model (K-Means, Hierarchical Clustering, K-Medoid Clustering), Validation (Connectivity, Dunn and  Silhouette indexes) |
| (Jang et al., 2021) | Electricity Load Profile | Smart Metering Data in 2009 | Identity, Social Status, age, gender, Demand kWh, Income | Regression Ordinary Least Square (OLS), Evaluation (Root Mean Square Error (RMSE)) |
| (Lee et al., 2020) | Electricity Load Profile | Residential Demand Data from November 2017 until February 2018 | Identity, Daily Consumption, Load Profile, Peak Hour, Demand | K-means, Fuzzy C-Means (FCM) and Self Organizing Maps (SOM) |
| (Gajowniczek & Zabkowski, 2018) | Electricity Consumption Forecasting | Electricity Consumption Data from 46 homes in Texas | Identity, Time, Total kWh | Model (Artificial neural networks, regression  trees, random forest regression, 𝑘-nearest neighbors' regression,  and support vector regression), Evaluation (Naive forecast, random  forecast, the ARIMA model, and stepwise regression) |
| (Bañales et al., 2021) | Electricity Demand with Renewable Technologies | Half-hourly energy use for one-year data | Average energy use,  energy–temperature correlation, the entropy of the load-shape representative vector, and distance to  wind generation patterns. | Model (K-Medoids), Validities (average silhouette) |
| (Afthoni et al., n.d.) | Electricity Consumption in Indonesia | Customer Transaction in September 2021 | Rate, Power, Total kWh, Total Cost, Flash Time | Variable selection with correlation  Model (K-Means)  Validity (Silhouette Method)  Explores (Customer Relationship Management (CRM)) |

Previous studies in customer segmentation in electricity consumption have explored various dimensions of the customer clustering problem (McLoughlin et al., 2015); (Camero et al., 2018);(Gajowniczek & Zabkowski, 2018); (Lee et al., 2020). They use the context of electricity consumption as a case study to find out patterns of electricity use in predicting future electricity consumption. Several clustering models, one of which is often used, namely K-Means Clustering, have been explored customer grouping by considering patterns of electricity use and electricity demand to meet electricity consumption based on what has been prepared by the company (Ye, 2021);(Jang et al., 2021).

A context study of load profile electricity (McLoughlin et al., 2015) using experimental data by installing 4000 intelligent meters in several homes in Ireland with existing methods used to classify household electricity use, in general, can be divided into four categories, statistics, manipulation, time series, and clustering. Statistical methods have been widely used in the unregulated power market to form a standard load of Personal Classes (PC). A typical load PC is used for settlement purposes and estimates the amount and time of electricity used.

Research on electricity consumption in South Africa (Toussaint & Moodley, 2020) focuses on household customers, aiming to classify customers based on patterns and types of using electricity using the K-Means clustering model and Self Organizing Maps (SOM). They used internal and external validation to evaluate the clustering structure based on South African households expected daily electricity consumption behavior. Another study used electrical load data also in Andalusia, Spain (Camero et al., 2018), but the research context was about electricity demand. Using a combination model between K-Means clustering and K-medoid clustering, they determine interrelated variables to predict customer segmentation. This study aims to provide an alternative customer segmentation that can manage several types of customers. It then presents the segmentation results based on the characteristics of the load curve. Finally, they compare the two marks and provide solutions to the effects of classification and segmentation.

Research on the context of electricity load data (E. Lee et al., 2020) uses electricity demand data to predict electricity loads per day based on customers' heterogeneity of electricity demand behavior, then processed using a combination of K-Means clustering models and Self Organizing Maps (SOM) and Fuzzy C-Means. The segmentation results provide the proper group identification for electricity demand per day. The result shows a tremendous impact because it can save on utility costs based on electricity reduction by customers. Another study with the same context as (E. Lee et al., 2020), but this study uses data from smart meters in 2009 (Jang et al., 2021), they use a regression model with an evaluation of the root mean square error for customer segmentation based on electricity demand used, age, and Income from the customer. The aim is to find new customer electricity usage behavior patterns based on predetermined variables. Another study uses six regression models to predict daily electricity consumption based on the total electricity consumption used by customers (Gajowniczek & Zabkowski, 2018). They compared the models to find new patterns of customers' daily electricity usage.

Research on the context of looking for energy reserves based on the number of customer electricity requests (Bañales et al., 2021) uses data on customers' half-day electricity usage by selecting variables based on the average amount processed by adding wind variables as alternative electrical energy. This study uses the K-Medoid model and the Silhouette method to validate the number of clusters to apply an efficient time series clustering methodology that explicitly considers the pattern of renewable energy generation. Other research on the context of electricity consumption in Indonesia (Afthoni et al., n.d.). They used data on customer electricity bills in September 2021 with predictors of power, rate, total kWh, flash sale, total cost, tested for variable correlation. This research uses the K-Means Clustering model and the Silhouette Method as the number of clusters to get customer segmentation based on the characteristics of customers paying for electricity according to the power used. The clustering results will be explored using the CRM model to gain insight into customer action in the future according to the wisdom that has been carried out.

**1.2 Customer Lifetime Value in Customer Segmentation**

Previous studies in customer segmentation have explored various dimensions of customer clustering problems (Gustriansyah et al., 2019; Janardhanan & Muthalagu, 2020; Marisa et al., 2019). Many of them use the marketing context as a case study. The K-Means clustering model and Customer Lifetime Value explores customer grouping by considering the specified product preferences and predicting customer behavior in buying products offered by the company (Z. J. Lee, Lee, Chang, & Sano, 2021)

A context study in marketing combines the Customer Lifetime Value (CLV) and K-Means models in each customer segment (Marisa et al., 2019a). The grouping uses the K-Means Clustering method based on the LRFM (Length, Recency, Frequency, Monetary) model. The cluster formation process uses the Elbow method. The CLV value is generated from the multiplication of the LRFM normalization results, and then the LFRM weight value uses the Analytical Hierarchy Process (AHP). Based on the LRFM matrix, this cluster has a high loyalty value, with the symbol LRFM being a loyal customer (the best segment with a high customer loyalty value). Based on the LRFM symbol, companies can create strategies to retain customers and acquire loyal customers with high profitability.

Another study with a supermarket marketing context with the same objective and predictor variables used historical customer data processed with a combination of LRFM models to determine data selection on potential customer purchases (Z. J. Lee et al., 2021). The K-means clustering model to map customers based on the same characteristics is then classified to distinguish potential customers for repurchase and then validated using the elbow method. This study uses data from all AR-Pulsabiz pulse server operators in Malang, Indonesia, to predict the future of Small and Medium Enterprises. The number of potential customers who will become operators by using a combination of the K-Means Clustering model and the LRFM model to group customers to provide services according to priority.

Research in pharmaceutical marketing (Gustriansyah et al., 2019) also has the same objective (Marisa, Ahmad, Yusof, Fachrudin, & Aziz, 2019b), but they use eight validation methods in determining the correct number of groupings. Another transportation survey uses the K-Means Clustering model and the CLV model to group customers (Li et al., 2018) with the same research objective (Ye, 2021). It also has similar goals and models (Ye, 2021) to marketing research in Telecommunication Companies (Abdi & Abolmakarem, 2019). However, they do not use the CLV model but use the Neural Network to classify priority customers after getting the results from clustering.

**1.3 Marketing Strategy in Customer Relationship Management**

Two popular customer relationship strategies can lead to an increase in profits and customers retention (Hosseini et al., 2010), namely:

1. Sustainable Marketing

This program is a program to maintain and increase customer loyalty through special long-term services and increase value by studying the characteristics of customers (Cunha et al., 2020; Foncubierta-Rodríguez et al., 2020; Malm et al., 2020; Rao et al., 2020). Implementing a sustainable marketing program from this concept will be explained as follows.

1. Continuous Replenishment Program

This program is used for less profitable customers (Tsao, Setiawati, Linh Vu, & Sudiarso, 2021). Approaches to programs such as partnership programs encourage increased use of the company's services to customers (Tsao et al., 2021).

1. Business to Business

This program is used for profitable customers (Foncubierta-Rodríguez, Galiana-Tonda, & del Mar Galiana Rubia, 2020; Rao, Velidandla, Scott, & Drechsel, 2020). The approach to this program is like providing special executive services to customers to improve service, so that customer trust will increase and become more loyal (Baniasadi et al., 2021; Daat et al., 2021; Xie et al., 2021; Yan et al., 2018).

2. One to One Marketing

This program is an individual program that satisfies customers' unique needs (Gil-Quintana & Vida de León, 2021; Kafkas, Perdahçı, & Aydın, 2021). This program uses customer information from online news and databases, followed by personal interactions to meet customers' unique needs (Baniasadi, Samari, Hosseini, & Najafabadi, 2021; Xie, Chen, Huang, & He, 2021). Build interactive marketing and post-marketing programs in developing customers using individual customer information (Huynh et al., 2021; Koponen et al., 2021; Yudhya, 2019). The application of the one-to-one marketing program from this concept will be explained as follows.

1. Customer Business Development

This program is used for profitable customers (Borisavljević & Radosavljević, 2021; Daat, Sanggenafa, & Larasati, 2021) by assessing the benefits of marketing, finance, and management business processes (Koponen, Julkunen, Gabrielsson, & Pullins, 2021; Kulej-Dudek, 2021). This program aims to explore the customer's business development by providing the best solutions and consulting regarding customers' services (Borisavljević & Radosavljević, 2021; Kulej-Dudek, 2021)

1. Retail Account Marketing

This program is used for less profitable customers (Yan et al., 2018; Yudhya, 2019). The approach to this program sees the customer as a partner to develop business opportunities. This program performs customer profiling further by using CRM, which is more integrated into the application (Dias, de Oliveira, Filho, & Rodrigues, 2021; Sekizaki, Nishizaki, & Hayashida, 2016).

To the best of our knowledge, most previous studies on customer segmentation on electricity consumption focus on predicting electricity consumption and electricity demand per day used by customers because it affects electricity supply or looking for other electricity alternatives. Previous research focused on household customers by identifying daily electricity consumption (Afthoni et al., n.d.; Gajowniczek & Zabkowski, 2018; Toussaint & Moodley, 2020), electricity load profile (Jang et al., 2021; E. Lee et al., 2020) and daily electricity demand (Bañales et al., 2021; Camero et al., 2018; Hyland et al., 2013). Then, only one study combined the concept of clustering with CRM (Afthoni et al., n.d.); the other research only compared the clustering model to find patterns of electricity use. However, in the idea of clustering electricity consumption for customer segmentation, no one has analyzed based power, peak-load electricity consumption and off-peak-load electricity consumption and then combined them with the concept of CLV (Marisa et al., 2019) to determine the correct customer group. In this study, clustering was carried out using the K-Means method, with the number of clusters being validated using the Elbow method. Then, the clustering results will be classified using CLV. Calculation of CLV will involve the value of the clustering variable and the weight value of the clustering variable value. The weight value will be calculated using the Analytical Hierarchy Process. The results from the CLV will be used to determine marketing strategies based on the concept of Customer Relationship Management on the right customer segmentation results to develop the company's services in the future.

**2. METHODS**

Figure 1 presents the research framework of this study. The framework is adapted from standard methods for building predictive analytical models (Schoenherr & Speier-Pero, 2015). There are five stages: data collection, data preparation, choice variables, clustering model, marketing strategy.

**2.1. Data Collection**

In this study, we used data from PT. PLN Persero. of the West Sumatra zone. Our research uses customer transaction data from January 2019 to December 2020, consisting of 16,504,228 and 107 data variables. Table 2 shows the data that has been taken from 2 years.

**Graphical user interface, diagram, application

Description automatically generated**

**Table 2.** Result of data collection

|  |  |  |  |
| --- | --- | --- | --- |
| Data | Year | Row | Variable |
| Customer Transactions history | 2019 | 7,945,689 | 107 |
| Customer Transactions history | 2020 | 8,558,539 | 107 |

**2.2. Data Preparation**

This section presents the data preparation processes for developing the prediction model, namely:

A. Data Profiling

This section presents the focus of the data, which will be selected based on the data analysis to be carried out. The study starts by looking at the areas in West Sumatra that use the highest electricity. Figure 2 presents based on the results of the plot analysis that has been carried out in 4 areas of the service center of PT. PLN Persero, the Padang area, has the highest electricity consumption compared to other sites.

The subsequent analysis looks at potential customers who use higher total kWh. Figure 3 presents the results of plot analysis based on total electricity consumption by customer category. Based on the regulations issued by the Indonesian government [48], customers are divided into five categories, namely household, social, government, business, and industrial. Based on the results of the analysis plot that business customers have carried out, the highest use of electricity is around 37%, followed by industrial customers as much as 31% and other customers using electricity consumption below 15%. Therefore, this study focuses on business customers because they use higher electricity consumption than others and can increase company revenues.

B. Data Cleaning

This section presents a further analysis of the data focuses carried out previously. This analysis is used to clean or remove data rows if duplicate data rows or missing data rows. The results of data cleaning will find potential predictor variables based on the number of data variants contained in the variable. Finally, Table 3 shows the analysis results of data focus and data cleaning obtained 13 variables with 508,934 data records used for model development.

**Figure 2.** Total electricity consumption based on region

**Figure 3.** Total electricity consumption based on customer category

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Data Type | Count | Max | Min | Variable Description |
| ID Customer | Integer | 24,785 | - | - | Identity of the customer |
| Customer Service Unit | String | 12 | - | - | Customer Service Units or service branches provided by the company which are in 4 customer service centers namely Belanti, Painan, Indarung, Pariaman, Lubuk Basung, Lubuk Sikaping, Koto tuo, Baso, Sijunjung, Sungai Rumbai, Kayu Aro, Sawah Lunto, Batusangkar, Lintau, Lima Puluh Kota and others |
| Data Entry Date | Date | 24 | 2020/12 | 2019/01 | Admin enters data per 1 month |
| Rates | Categorical | 3 | - | - | B1 means a business that uses electricity from 450 kWh to 5500 kWh, B2 means a business that uses electricity from 6600 to 200 thousand kWh, B3 means a business that uses 200 thousand kWh of electrical power and above |
| Power | Integer | 43 | 2,425,000 | 450 | Power used by customers such as 450 kwh,900 kwh,1,300 kwh, 2,200 kwh,3,300 kwh, 7,700 kwh,15,400 kwh,132,000 kwh, 200,000 kwh and others |
| Meter Code | Categorical | 5 | - | - | M means analog meter, and E means the digital meter |
| Flash time | Double | 2,7904 | 4775.66 | 0 | Electricity usage time by customer |
| Total KWH | Integer | 1,0427 | 635,370 | 0 | The total peak load kWh usage and peak external load kWh used by customers |
| KWH Off – Load | Integer | 10,417 | 500,640 | 0 | KWH used at peak external load by customers |
| KWH Peak Load | Integer | 1,515 | 146,580 | 0 | KWH used at peak load by customers |
| Discount | Double | 11 | 338,942 | 0 | The company gives discounts based on the provisions of the company, such as using unused kWh by the company or because of a natural disaster |
| Peak Offload Fee | Double | 18,578 | 518,552,899 | 0 | Payments made when using Peak Offload |
| Peak Load Fee | Double | 2,256 | 227,736,949 | 0 | Payments made when using Peak Load |
| Total Cost | Double | 21,621 | 732,079,768 | 0 | The total cost paid by the customer |

**Table 2.** Result of data collection

**2.4. Choice of Variabel**

This section presents predictor variables that will later be used in the clustering model. From the 13 variables in Table 3, the variable to be selected is of type Integer or Double because the process in the clustering model focuses on predicting customer segmentation on power based on peak load and peak external load used by customers in the future. Still, the ID\_Customer variable is not included in the predictor because this variable is not needed in the clustering model. This research will expect the peak load, which the usage time is from 6.00 am to 4.59 pm, and the peak external load, which is from 5.00 pm to 5.59 am (Permen ESDM 31 Tahun 2014\_TARIF TENAGA LISTRIK, n.d.). Based on this explanation, the kWh off-loads, and kWh Peak Load variables are used as predicted in the clustering model. Table 4

shows nine possible variables used in the clustering model.

**2.4. Rapid mixing and neutralization basin (physicochemical treatment)**

Nam feugiat ultrices nulla non facilisis as shown in **Figure 3**, Duis pellentesque sem sed nulla rhoncus, sit amet ultrices urna fermentum. Nam at est in massa lobortis finibus sit amet sit amet augue. Aenean iaculis, metus vel fringilla feugiat, nisl nisi ullamcorper odio, quis consectetur augue elit vel mauris. Curabitur sed ipsum id tortor accumsan aliquet a nec justo. Mauris blandit eleifend ante, vulputate tempor risus laoreet vitae. Nullam malesuada accumsan scelerisque. Aliquam erat volutpat. Vivamus sed diam erat. Pellentesque ullamcorper arcu eu orci finibus, vel feugiat tellus laoreet. Ut bibendum justo sit amet odio convallis, vel tincidunt enim maximus.

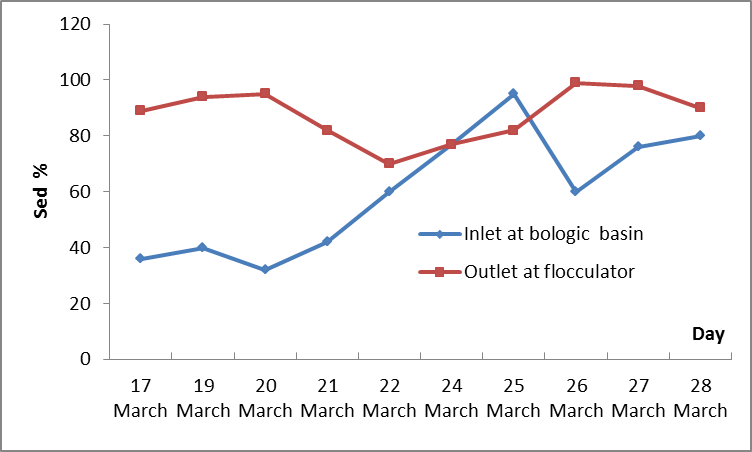
**3. RESULTS AND DISCUSSION**

**3.1. Temperature**

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**Table 1.** The COD and BOD values for the last week of the month (final clarification output).

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **FINAL CLARIFICATION OUTPUT** | | | | | | | | | | |
| **Day N°1** | | **Day N°2** | | **Day N°3** | | **Day N°4** | | | **Day N°5** | |
| COD  mg/ | COD  mg/ | COD  mg/ | COD  mg/ | COD  mg/ | COD  mg/ | | COD  mg/ | COD  mg/ | COD  mg/ | COD  mg/ |
| 130 | 36 | 162 | 44 | 153 | 28 | | 160 | 32 | 167 | 39 |



**Figure 12.** Daily variation in the sedimentation of the sludge at the outlet of the WWTP flocculator.

**4. CONCLUSION**

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**5. ACKNOWLEDGMENT**

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**6. AUTHORS’ NOTE**

The authors declare that there is no conflict of interest regarding the publication of this article. Authors confirmed that the paper was free of plagiarism.

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