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Optimize Billing Routes for Distance Minimization Using Qaco: Qgis Mapping and ANT Colony Optimization (ACO) Algorithms

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Abstract
The acceleration of PLN's cash-in performance is significantly influenced by customers' early payment behavior. Therefore, PLN requires a solution to shift the payment pattern of customers who frequently delay payments into making timely payments before the due date. One of the main causes of payment delays is the limited availability of payment counters, as well as customers forgetting to pay their electricity bills. This study analyzes customer electricity payment patterns over a six-month period at PLN ULP X, which is part of PLN UP3 XYZ. The analysis revealed that 7.87% of customers are recurring late payers, dispersed across various locations. To address this issue, a preventive collection strategy is required to reduce the occurrence of late payments. However, the implementation of preventive collection faces time constraints, as billman officers have limited availability due to other responsibilities. Thus, a supporting tool in the form of route planning is needed to minimize travel distance. In designing the collection route, the Traveling Salesman Problem (TSP) model is applied using geographic mapping through QGIS and optimized with the Ant Colony Optimization (ACO) algorithm. QGIS is used to map the distribution of late-paying customers based on geographic conditions. The study results show that the ACO algorithm successfully reduced the total travel distance to 1,022 km, compared to the existing condition of 4,300 km, resulting in a distance saving of 3,278 km (76.23%).

INTRODUCTION

PT PLN (Persero) is a State-Owned Enterprise (*BUMN*) that conducts the business of providing electricity for the public interest in adequate quantity and quality, as well as fostering profits and carrying out government assignments in the electricity sector to support development by applying the principles of a limited liability company. The government's assignment in supporting development is the business process of generating, transmitting, and distributing electrical energy to people in all corners of Indonesia (Amalia et al., 2024; Handayani & Nugroho, 2022; PLN, 1995). In the implementation of buying and selling electricity with customers, PLN always provides optimal quality service (Chughtai & Iqbal, 2018; Leksyutina, 2019; Wahyudi et al., 2020). In 2008, PLN launched a new electricity service product, namely prepaid electricity; this was a breakthrough step to provide customers with the opportunity to choose the product they want (Ratuva, 2017; Stepanova, 2018; Sutter, 2018). Thus, PLN has two types of customer service products, namely postpaid services and prepaid services. *Postpaid* services use a conventional business model run by PLN, where customers enjoy electricity consumption first and pay at the end (Akaha & Hirata, 2021; Brissenden & Clayfield, 2016; Thu, 2020). Therefore, every month PLN must record meters, calculate and issue electricity bill accounts, and also bill electricity accounts to customers for electricity consumption, as well as disconnect electricity if customers are late in paying their electricity bill obligations for the current month (Chong, 2017; Feng, 2019; Motaher & Khaled, 2025).

One of the Customer Service Implementation Units (*UP3*) in Indonesia, namely PLN *UP3 XYZ*, as of August 2024, manages 327,062 customers, with a composition of 258,639 prepaid customers (78.08%) and 68,423 postpaid customers (20.92%). Of the postpaid customers, 62,064 (90.71%) paid by the 20th, while 6,359 (9.29%) paid after the 20th (in arrears). These delinquent customers are influenced by several factors, namely customers forgetting, electricity bills not being a top priority, and limited electricity payment counters in the customer area. The location of PLN customers in the units in *UP3 XYZ* that are in arrears is scattered. PLN hopes that customers understand the consequences, as explained through the *Electricity Sale and Purchase Agreement* (*SPJBTL*) at the beginning of the new installation application, which includes points about the consequences related to the customer's negligence in paying electricity bills. If the billing schedule limit is exceeded on the 20th, then PLN has the right to make a temporary termination (*TUL VI-01*). If, 60 days after the temporary termination, the customer has not paid off the arrears, then PLN has the right to unilaterally carry out a complete dismantling. After the dismantling is completed, if the customer wishes to reconnect, the customer is required to pay off all unpaid obligations and will be treated as a new installation request. From the *SPJBTL*, the rules are quite clear: customers who have not paid off their electricity bill obligations beyond the 20th of each month will be subject to temporary disconnection sanctions for their electricity connections. However, if the customer has paid the arrears, then the connection will be restored (Hines & Bishop, 2015; Hines & Gold, 2014; Loi, 2020).

Field officers who carry out meter reading, billing, and both postpaid and prepaid customer termination work, namely *Billing Management* (*Billman*), work in meter reading, billing, and termination according to the *Meter Reading Route* (*RBM*) that has been determined based on the work order directed by the *Customer Service Unit* (*ULP*) without categorizing the type and amount of customer arrears. In its development, *billman* officers have an additional workload, namely prepaid customer checks and prepaid receivables customer billing, so there is a potential risk that postpaid electricity account billing work is not optimal. Based on this, it is necessary to optimize billing by establishing optimal customer billing routes as an effort to prevent potential defaults on PLN's electricity accounts. Based on the average number of delinquent customers who have not paid their electricity bill, which reaches 9.29%, with a fairly large bill amount averaging IDR 4,016,580,386, the current obstacle within PLN is that the billing route of *billman* officers in an effort to accelerate revenue has not been formed effectively and tends to be monotonous. There are also external factors, such as the geographical condition of customers who are spread out with an uneven number of customers, and social and cultural conditions in the community. Therefore, an optimal route is needed in preventive billing for customers who have a history of late payment of electricity bills in the last six months. *Preventive billing* is the activity of billing PLN customers' electricity accounts before the 20th, with the aim of shifting the habit of customers paying after the 20th to before the 20th. This will also help build a culture of PLN customers paying electricity bills earlier in the month.

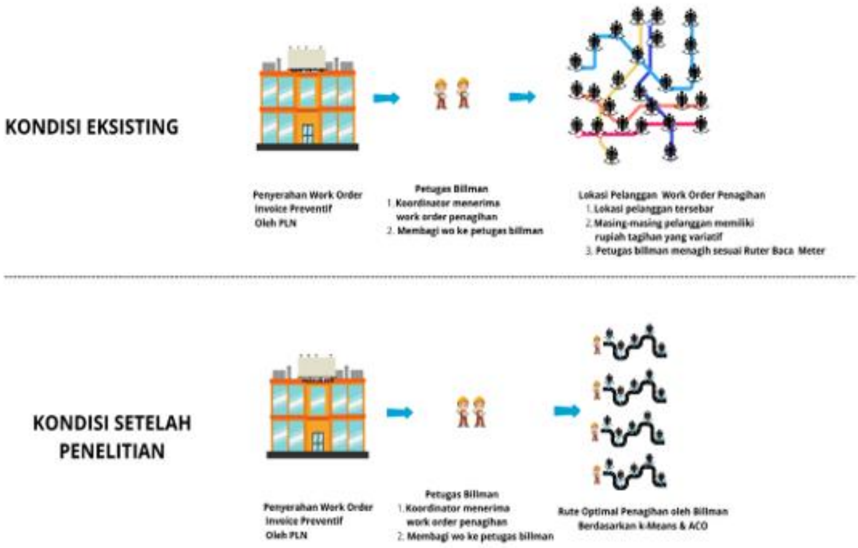

Figure 1. Mind Mapping Research

The image above illustrates the problem addressed in this study, namely the optimal route arrangement for *billman* in preventive billing, aimed at accelerating cash-in performance using *QGIS* and *Ant Colony Optimization* (ACO). A case study approach is used to analyze the behaviors and factors influencing PLN customers in paying electricity bills, drawing on several methods from previous research. For example, Wahyudi et al. (2020) applied the *Fuzzy Genetic Algorithm* to the *Traveling Salesman Problem* (TSP), with the objective of minimizing costs and distances to achieve optimal routing. Their findings showed that optimal route planning could save operational costs by up to 21.51%, although the study did not incorporate spatial distribution using Geographic Information Systems (GIS).

In another study, Handayani and Nugroho (2022) combined the *Firefly Algorithm* (FA) and *Ant Colony Optimization* (ACO) to optimize shipping routes in maritime logistics. The results demonstrated that hybrid algorithms could improve efficiency in constrained environments, but the research was limited to maritime logistics and did not examine consumer billing behavior. Additionally, a study using the *Ant Colony Optimization* method addressed the scheduling and routing of tanker trucks for park irrigation in Surabaya. The research concluded that optimal distribution could not be achieved if collection officers worked without direction, as this would slow down revenue collection from postpaid customers.

Large customer data, including payment history and characteristics, can be utilized to model optimal billing routes. The determination of the optimal route in preventive billing activities, particularly for customers with recurring delinquencies, involves mapping with *QGIS* and route optimization using the ACO algorithm, referred to as QACO. This study aims to map PLN postpaid customers with a history of recurring delinquency using *QGIS*, and to determine the shortest alternative billing route based on the mapping results through the ACO algorithm. Furthermore, the study will compare the billing routes generated by the ACO algorithm with existing routes that follow the *Meter Reading Route* (*RBM*).

The benefits of this research are multifaceted. For the company, it is expected to accelerate revenue, minimize the potential for delinquent customers, and increase the effectiveness of billing assignments by *billman*. For customers, the research aims to foster a culture of timely electricity bill payments, helping them avoid late payment fines. For the author, this study provides an opportunity to apply various theories and data modeling techniques to produce accurate analyses in response to the challenges faced by the company. This approach advances utility service optimization and supports digital transformation in route-based field operations.

METHOD

This research employed a case study approach, analyzing six months of customer payment data to identify recurring delinquent customers. The methodology began with an in-depth understanding of the customer dataset, which included critical information such as transaction dates, customer IDs, *Customer Service Units* (*ULPs*), addresses, meter reading routes, electricity tariffs, and bill amounts. This process aimed to identify payment distribution patterns and assess the frequency of payment delays. The dataset encompassed 2,384 customers and variables such as tariff type and electricity power.

Data modeling was conducted using the *Traveling Salesman Problem* (*TSP*) framework and the *Ant Colony Optimization* (*ACO*) algorithm to determine the most efficient billing routes for *billman* officers. The output analysis stage compared ACO-generated routes with existing conventional routes to evaluate methodological effectiveness. Sensitivity analysis was applied to assess the impact of key parameters—such as evaporation coefficient and visibility—on billing outcomes.

Customer data was grouped by criteria like delinquency frequency and geographical conditions to streamline optimal routing. The implementation combined *QGIS* software for spatial clustering and *ACO* for route calculations. Results demonstrated that the *ACO* algorithm generated shorter, more efficient routes compared to conventional methods, significantly enhancing billing process effectiveness.

RESULTS AND DISCUSSION

Research Object Profiles and Customer Data

This research was carried out in Customer Service Unit (ULP) X which is under the coordination of the Customer Service Implementation Unit (UP3) XYZ. This location was chosen because it has a fairly high level of customer payment delays and is representative of the problem of preventive billing in the national electricity system. Based on historical data from February to August 2024, information was obtained that as many as 2,384 postpaid customers were classified as customers with a history of three or more delinquencies. This is equivalent to 7.87% of the total postpaid customers at ULP X, with the cumulative value of arrears reaching IDR 695,552,879.

The customer data used includes the customer ID, the amount of arrears, the geographic coordinate points (latitude and longitude), and the Meter Read Route (RBM). Each customer entry stores critical information for the optimization modeling process, from cluster determination, distance calculation, to optimal route formation.

The characteristics of the geographical distribution of delinquent customers vary greatly, ranging from urban areas with good road access to sparsely populated hilly areas. In addition, the majority of customers who are in recurring arrears come from the R tariff group (households), indicating that the factor of late payment comes not only from financial ability, but also from limited access or discipline in payments.

Results of Clustering of Overdue Customers

The clustering process was carried out using Quantum Geographic Information System (QGIS) software, with an approach based on PLN's meter reading standards, namely dividing customers into medium areas (101–150 customers) and rare areas (50–100 customers). The results of the clustering showed that out of a total of 2,384 delinquent customers, 25 clusters were formed with a composition: 18 clusters for medium areas and 7 clusters for rare areas.

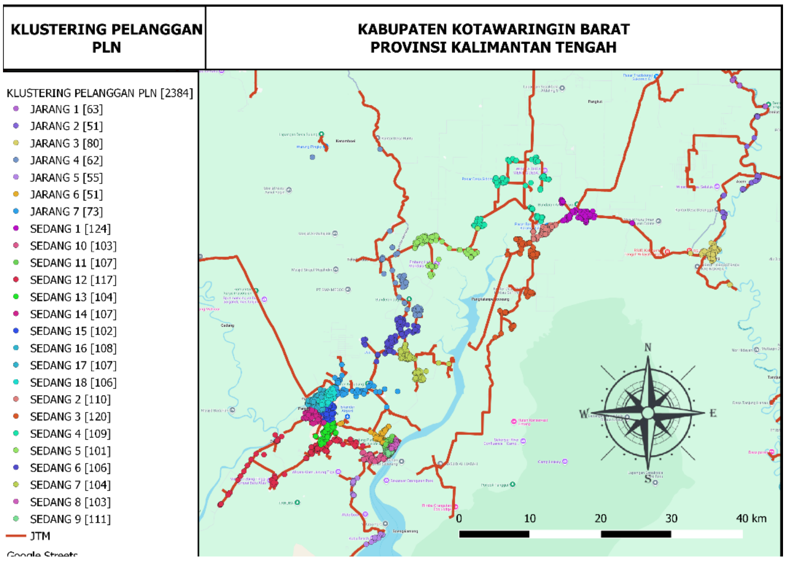

Figure 2. Results Customer clustering with QGIS

A visualization of the clustering results can be seen in Figure 2, which shows the spatial distribution of customers based on cluster categorization, which is helpful in efficiently arranging billing routes.

Simulation of Existing Routes vs Optimal Routes (ACO)

Two route formation approaches were used in this study, namely:

1. Existing Routes, which refer to the traditional Meter Reading Route (RBM), where the order of customers is administratively determined without considering mileage.
2. Optimal Route, which is generated from the implementation of the Ant Colony Optimization (ACO) algorithm with Traveling Salesman Problem (TSP)-based modeling.

For example, in Cluster 22, the existing route produces a mileage of 75.82 km, while the ACO route only reaches 16.94 km, which means that there is an efficiency of up to 77.67%. This decrease is very significant considering PLN's operational conditions, which have not optimized geographic-based billing routes.

Mileage Efficiency: Analysis Per Cluster

The following table presents a comparison of the mileage between the existing conditions and the ACO results for all 25 clusters.

Cluster	Existing Distance (km)	ACO Distance (km)	Efficiency (%)
1	839.78	123.88	85.24
2	193.22	46.92	75.71
3	94.31	29.13	69.10
…	…	…	…
25	98.04	15.41	84.27

The total mileage of the existing condition is 4,300.17 km, while the ACO optimization results only reach 1,022.35 km, which means that there is a total savings of 3,278 km or around 76.23% overall. This not only impacts time savings and operational costs, but also contributes to fuel efficiency and carbon emission reduction in field billing activities.

CONCLUSION

This research aims to design an efficient postpaid customer billing route through the integration of QGIS and Ant Colony Optimization (ACO) algorithms. The results show that this approach is significantly able to minimize mileage, with an average efficiency of more than 75% compared to existing methods. This confirms that the combination of spatial mapping and metaheuristic optimization is very effective in the context of billing operations in the electricity sector. The study's main contribution is the practical application of the ACO algorithm for route optimization in real-world scenarios, as well as its incorporation with geographic information systems that were rarely used simultaneously in previous studies. This approach opens up new opportunities to improve operational efficiency based on spatial data in the utility industry. However, the study has limitations, among other things, it has not taken into account real-time factors such as traffic or road conditions. In addition, the algorithm parameters have not been adaptively optimized. For future development, it is recommended to integrate dynamic data and hybrid algorithm exploration to support the implementation of a more flexible and responsive billing system.

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