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Optimal Scheduling of Electric Vehicle Charging: A Study Case of Bantul Feeder 05 Distribution System

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ABSTRACT

The growing popularity of electric vehicles (EVs) has the potential to complicate distribution network operations. When a large number of electric vehicles are charging at the same time, the system load can significantly increase. This problem is exacerbated when charging is done concurrently in the evening, which coincides with peak load times. To prevent the increase in peak load and distribution operation stress, EV charging must be coordinated to achieve financial and technical objectives. This study seeks to evaluate the impact of financially driven EV charging scheduling algorithms. The contribution of this study is that the scheduling algorithm considers EV usage behavior based on real data as well as considers the state-of-charge (SoC) target set by EV owners. The proposed algorithm seeks to minimize the total charging cost incurred by EV owners using mixed-integer linear programming (MILP). The impact of the coordinated charging scheduling on the system demand profile and real distribution system operation metrics are also evaluated. The simulation result tested on the Bantul Feeder 05 system demonstrates that coordinated charging can reduce the charging costs by 57.3%. Furthermore, the peak load is reduced by 5.2% while also improving the load factor by 3.5% as compared to uncoordinated scheduling. Based on the power flow simulation, the proposed algorithm can reduce distribution transformer loading by 0.5% and improve voltage quality by 0.1% during peak load. This demonstrates that coordinated EV charging benefits not only the EV users but also the distribution system operator by preventing system operation issues.

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1. INTRODUCTION

Electrical energy demand continues to increase every year since it is one of the indicators of the country's economic growth [1]. With rising energy demand accompanied with growing renewable energy generation, a management system that plays a role in maintaining energy efficiency is required. The advancement of information technology can be used to improve the efficiency of existing electric power systems [2]. This is commonly referred to as the smart grid. A smart grid, according to the Smart Grids European Technology Platform, is an electricity grid that is intelligently capable of integrating the actions of all users connected to it, including generators and loads, to produce a sustainable, economical, and reliable electricity supply [3].

Aside from being efficient, electricity generation is beginning to shift to new and renewable energy sources, reducing the use of traditional energy sources. Aside from electricity generation, other industries are beginning to shift to renewable energy sources. Transportation is one industry that is undergoing an energy transition [4]. The main factors driving transportation electrification are lower carbon dioxide emissions and less reliance on fossil fuels [5]. One of the transitions made is the substitution of electric vehicles (EVs) for fossil-fuel vehicles (EVs). Electric vehicles have various advantages, including being less expensive [6], lowering air pollution, and enhancing public health [7][8].

Despite some limitations, such as limited range, long charging times, and high battery costs, the use of EVs has increased [9]. More than 10 million electric vehicles were paved worldwide in 2020, a 43% increase from the previous year [10]. In fact, by 2030, the number of electric vehicles is expected to increase from 800 million to 1.6 billion [11]. Meanwhile, the Indonesian government has provided incentives to encourage the acceleration of the electric vehicle market in Indonesia. This is stated in Presidential Decree No. 55 of 2019 on the Acceleration of the Battery Electric Vehicle Program for Road Transportation [12].

If not managed properly, the penetration of a large number of EVs can pose system operation challenges. An increase in electrical load caused by charging electric vehicles can increase peak load demand [13], voltage deviation [14], and transformer deterioration [15]. To reduce the negative impact of EV penetration, it is necessary to manage and control EV charging.

The balance between demand and electricity generation on a smart grid is carried not only by the generation side but also by the customer side. Demand response is one solution for controlling load electricity consumption behavior [16]. Demand response is defined by the Federal Energy Regulatory Commission (FERC) as a change in customers' electricity consumption patterns as a result of a response to electricity rates or incentives, to reduce electricity consumption when electricity rates are high [17].

Electric vehicles cannot participate in the demand response program individually but must be part of a fleet group. An aggregator agent is required to enable interaction between a group of EVs and the grid [18]. The EVs aggregator's job is to buy electricity to meet the charging needs of managed EVs [18]. If an aggregator can control the charging process in EVs, it has the potential to improve system performance. Setting the charging time for electric vehicles at other times, such as at night until early morning can reduce charging costs due to low electricity rates at that time while also reducing grid operation stress.

Many studies on the optimal scheduling of electric vehicle charging have been conducted in recent years. By taking into account the system power flow, researchers [19] integrated electric vehicle charging stations into the economic dispatch process. However, the charging load of EVs is a variable that is optimized independently and is not based on consumer EV usage behavior. The charging behavior of each EV must be considered when scheduling EV charging. Researchers [20]–[22] developed an EV dispatching charging strategy based on EV user behavior such as time of arrival and departure, SoC at arrival, and desired state-of-charge (SoC).

Optimization must take into account not only the user behavior of EVs but also the applicable electricity pricing scheme. Electricity rates are especially important in the EV charging scheduling study [23]. Time-of-use (ToU), real-time pricing (RTP), and critical peak pricing (CPP) are three models of variation in electricity rates that are popular among policymakers and scientists [24]. Real-time pricing is used by researchers [21] to optimize charging costs, while ToU policy is considered by researchers [20], [25], [26]. Time-of-use means that different rates are applied at different times [27], such as when the peak load of electricity costs is higher. When compared to fixed-price (FP) tariffs, the study in [26] shows that ToU rates can have a positive impact on system load patterns even when EV penetration is high.

This study aims to develop optimal scheduling of electric vehicle charging with the study case in one of the distribution systems in Indonesia. The purpose of the optimization is to minimize charging costs incurred by the customers. The following is the present study's contribution:

1. Scheduling EV charging by taking into account EV usage behavior and desired SoC using mixed-integer linear programming (MILP) optimization.
2. Evaluating the influence of EV charging strategies on the load profile and distribution system's power flow security, including transformer loading and voltage profiles.
3. To the best of the authors' knowledge, this is the first study to use a case study on the Indonesian distribution system as well as statistical data on vehicle usage behavior in Indonesia.

The remainder of this paper is structured as follows. Section 2 describes the objective function of optimization, as well as its constraints and case studies. Section 3 presents and reviews the research findings comprehensively, and Section 4 draws conclusions from the proposed research.

2. METHODS

2.1. Optimization of EV Charging Scheduling

EV charging scheduling optimization is carried out to minimize the total charging cost of a number of EVs (NV) throughout a certain time horizon (NT). The factors that affect the charging cost is the charging power (${P_{ch}}_v^t$), electricity rates during a specific time window (${e_p}^t$), and the timestep per hour (t_s). The objective function of the optimization problem is shown in (1).

$$\text{Min } C = \sum_{t=1}^{NT}\sum_{v=1}^{NV} P_{ch_v}{}^t \cdot \frac{e_p{}^t}{t_s} \quad (1)$$

Optimization is carried out by considering several constraints, namely the charger power rating, battery capacity, the arrival and departure times of electric vehicles, and desired SoC. The constraints considered are shown in (2)-(6). Equation (2) limits the charging power of EVs ($P_{ch_v}{}^t$) to the capacity of the charger ($P_{ch\_max_v}$). The variable $v_{ch_v}{}^t$ is the charging state of the EVs. As stated in (3), during the arrival hour until the time the battery is fully charged, the charging state is labeled as 1. Otherwise, it is 0.

$$P_{ch_v}{}^t = v_{ch_v}{}^t \cdot P_{ch\_max_v} \quad (2)$$

$$v_{ch_v}{}^t = \begin{cases} 1, & t_v^{arrival} \le t < t_v^{arrival} + T_{ch_v} \\ 0, & otherwise \end{cases} \quad (3)$$

Equation (4) states the EVs SoC (SoC_v^t) under certain conditions. When the EV hasn't arrived home ($t < t_v^{arrival}$), the SoC is zero. When the time of arrival ($t = t_v^{arrival}$), the SoC equal to the arrival SoC ($SoC_v^{arrival}$). Finally, between arrival and departure times, the SoC follows the battery charging function, which depends on the charger power capacity ($P_{ch_v}{}^t$), battery capacity (E_{max_v}), charging efficiency (η_v), and timestep per hour (t_s).

$$SoC_v^t = \begin{cases} 0, & t < t_v^{arrival} \\ SoC_v^{arrival}, & t = t_v^{arrival} \\ SoC_v^{(t+1)} - \eta_v \cdot P_{ch_v}{}^t \cdot \dfrac{100}{t_s \cdot E_{max_v}}, & t_v^{arrival} \le t < t_v^{departure} \end{cases} \quad (4)$$

In (5), the variable T_{ch_v} is the required amount of to charge from the initial SoC ($SoC_v^{arrival}$) to the desired SoC (SoC_v^{target}). Meanwhile, in (6) the total charging status ($v_{ch_v}{}^t$) between arrival and departure time is equal the required charging time (T_{ch_v}).

$$T_{ch_v} = floor\left(\frac{SoC_v^{target} - SoC_v^{arrival}}{\dfrac{1}{t_s} \cdot \dfrac{\eta_v \cdot P_{ch\_max_v}}{E_{max_v}} \cdot 100}\right) \quad (5)$$

$$\sum_{t=t_v^{arrival}}^{t_v^{departure}-1} v_{ch_v}{}^t = T_{ch_v} \quad (6)$$

To model the optimization problem, a MILP approach is used. Python 3.8.3 is used for programming, using Spyder 4.1.4 as the integrated development environment (IDE). The CPLEX Studio 20.1 solver is utilized to identify the optimum solution using an Intel Core i7-8550U and 16 GB RAM PC.

Research Workflow

Fig. 1 depicts the workflow of this study. The research begins with the development of a test system to evaluate the proposed optimization method. The developed EV charging scheduling method was tested on a distribution system in Bantul Regency, Yogyakarta Special Region, Indonesia. The system used is one of the feeders at the Bantul Substation, namely the Bantul 05 Feeder. This system is a radial distribution system with a voltage level of 20 kV. Technical details of this system can be found in [28]. The system is then modeled in the power system simulator package DIgSILENT PowerFactory 2022 [29]. Fig. 2 depicts the single-line diagram of the testing system used.

Then, the data that will be used as input for optimization were collected, such as the system's load profile, electricity rates, considered EV types, and EV usage patterns. Fig. 3 shows the system's load profile used in this study. The Feeder Bantul 05 has an installed load of 8123 kW and a peak load of 5946.7 kW. It is assumed that all loads have the same load profile. The electricity rates used in the optimization follow the ToU rates proposed in [30]. With this tariff scheme, daily electricity rates will be divided into three windows, i.e., off-peak, medium, and peak as shown in Fig. 4.

It is assumed that 150 EV charging units are installed in the system. The EVs charger under consideration here is assumed to be installed in every home for charging the private vehicle. Because private vehicles are more dispatchable than public transportation, they were chosen as a case study. Furthermore, private vehicle owners can choose whether to participate in the EVs charging scheduling program [31]. To simulate charging patterns for electric vehicles, some vehicle usage data, namely departure and arrival hours, as well as the distance traveled from each electric vehicle, is required. The three data are generated randomly based on the distribution obtained from the Jabodetabek 2019 Commuter Survey [32]. Fig. 5 shows the time of arrival and departure distribution, while Fig. 6 illustrates the distribution of daily EVs mileage.

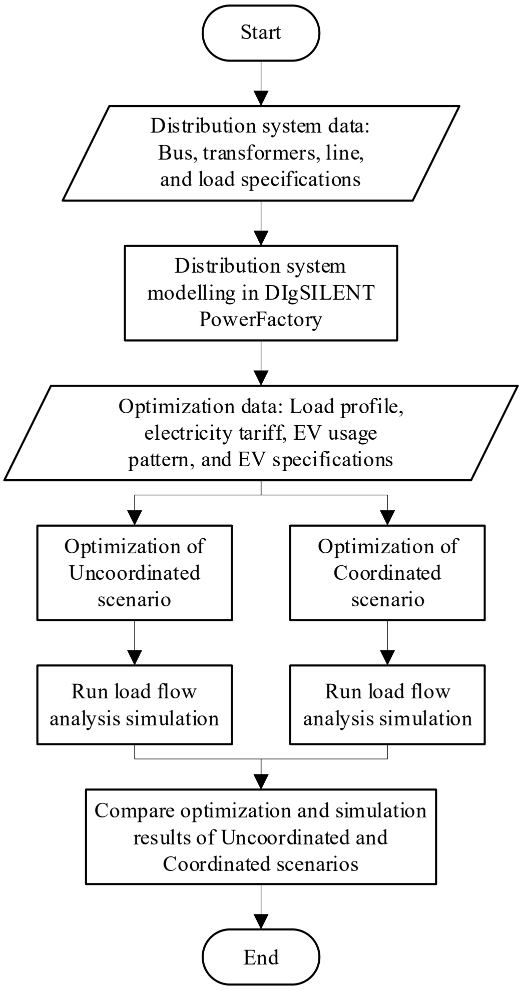

Fig. 1. Research workflow

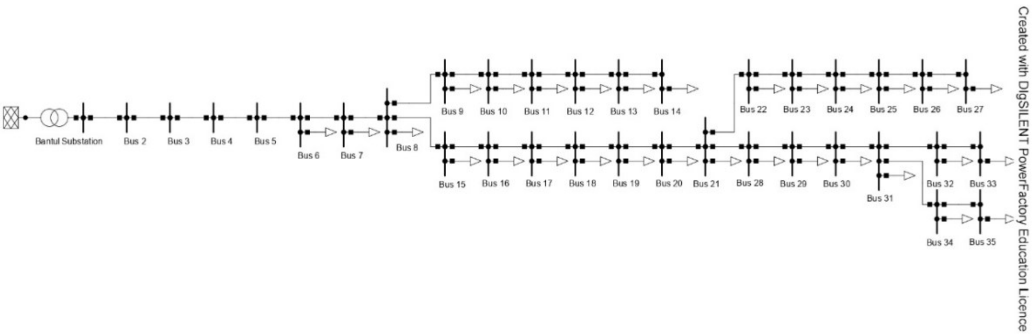

Fig. 2. Bantul Feeder 05 single-line diagram

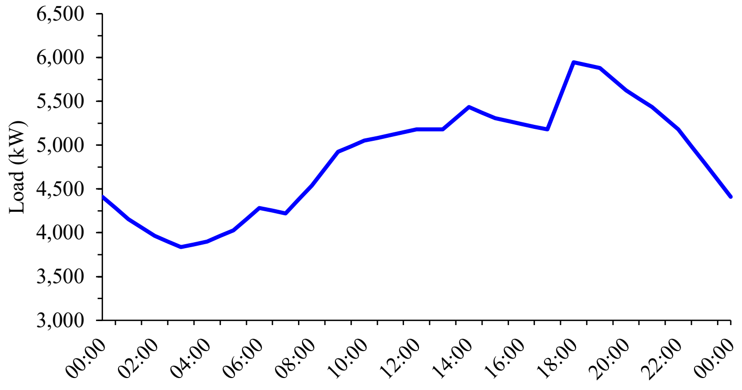

Fig. 3. System's load profile

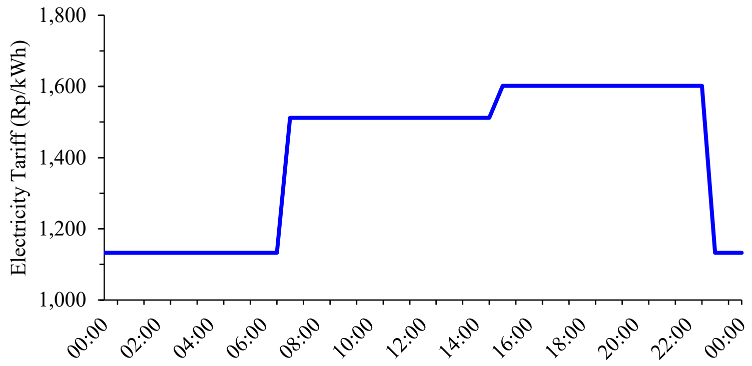

Fig. 4. Hourly electricity tariff

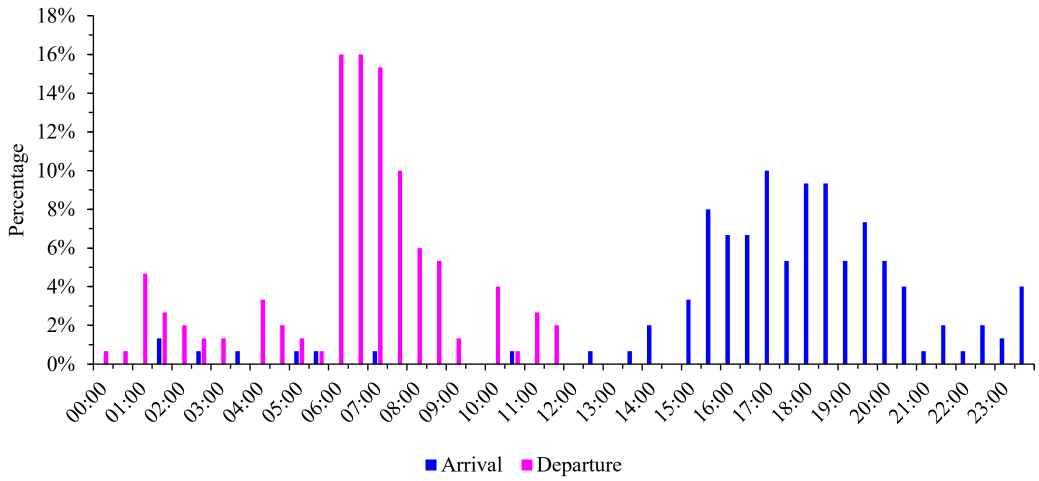

Fig. 5. Time of departure and arrival distribution

The vehicle mileage data is converted to the remaining SoC. As a result, data on each EVs battery capacity and energy consumption is required. The Hyundai Ioniq 5 (Standard Range), Hyundai Kona Electric, Nissan Leaf, Genesis G80, and Lexus UX 300e are among the five EVs under consideration. Table 1 summarizes the technical data for each vehicle type taken from [33]. The charger capacity of electric vehicles is adjusted to the specifications of each EV, with assumed charging efficiency of 90%. Fig. 7 depicts the results of converting mileage to remaining SoC.

Table 1. EV model and technical specifications [33]

EV Model	Charger Power (kW)	Battery Capacity (kWh)	Energy Consumption (kWh/km)
Hyundai Ioniq 5 (Standard range)	11	54	0.183
Hyundai Kona Electric	7.2	39.2	0.157
Nissan Leaf	3.6	39	0.166
Genesis G80	11	82.5	0.188
Lexus UX 300e	6.6	45	0.191

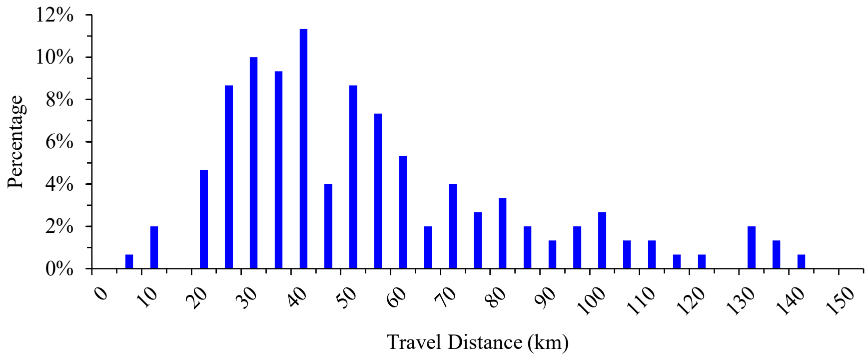

Fig. 6. EVs daily milage distribution

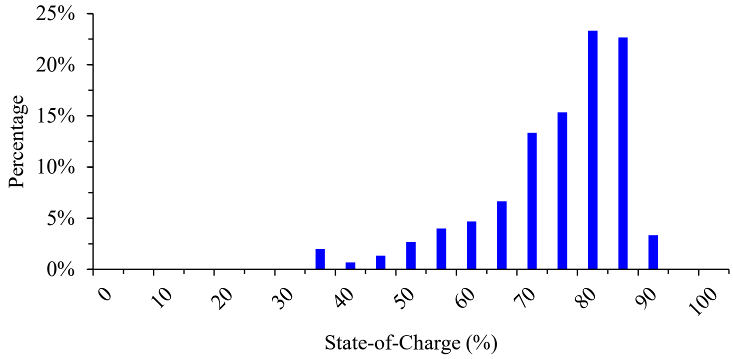

Fig. 7. SoC distribution at the time of arrival

The 150 EV chargers are assumed to be distributed evenly across 15 buses. This means that each bus has ten EV charging stations. The total capacity of the EV chargers installed in the system is 1182.4 kW, which is approximately 20% of the system's peak load. The distribution of charger capacity on each bus is shown in Table 2.

Table 2. Installed EV charger capacity at each bus

Bus	Installed Charger (kW)	Bus	Installed Charger (kW)	Bus	Installed Charger (kW)
Bus 8	94.4	Bus 15	70.8	Bus 28	86
Bus 9	61	Bus 16	75.2	Bus 31	94.4
Bus 11	91.2	Bus 21	71.4	Bus 32	86.2
Bus 12	88.6	Bus 25	70.8	Bus 33	87
Bus 14	66.4	Bus 26	60.2	Bus 35	78.8

Two charging scenarios were observed to test the developed method: Uncoordinated and Coordinated. Uncoordinated charging indicates that the drivers will immediately charge their EV once arrive home. When the battery percentage is close to 100%, charging will stop. Meanwhile, coordinated charging indicates that the charging is determined at a specific time based on the optimization. This means that even if the vehicle is connected to the charger, the charging process may be delayed rather than completed immediately. The SoC target is limited to 90% based on [34][35] as a high level of SoC is strongly linked to battery life degradation [36]. Table 3 provides a summary of the scenarios considered in this study.

Table 3. Optimization scenarios

Scenario	Charging Start Time	Charging End Time
Uncoordinated	When the EV arrives at home	Battery SoC ~100%
Coordinated	Based on optimization	Battery SoC ~90%

After the optimization result of both scenarios were obtained, a power flow analysis simulation was then performed to evaluate the impact of the Uncoordinated and Coordinated charging scenarios on the distribution system. There are two measurements taken, namely transformer loading and voltage on Bus 35, which is the bus furthest away from the transformer. This bus was chosen because it is the bus that experiences the most undervoltage. Table 4 displays the security criteria references used for comparison.

Table 4. Power flow security criteria

Parameter	Value	
	Minimum	Maximum
Transformer loading [37][38]	-	80%
Bus voltage [39][40]	0.9 p.u.	1.05 p.u.

3. RESULTS AND DISCUSSION

3.1. EV Charging and Load Profile

The charging pattern in both scenarios is depicted in Fig. 8. Heavy charging occurs between 15:00 and 22:00 in the Uncoordinated scenario, with peak charging at 19:00. This occurred because many drivers arrived home at the time and immediately charged their EVs. Furthermore, charging during these times occurs when electricity rates are high, potentially increasing charging costs. In the Coordinated scenario, however, most charging occurs between 23:00 and 06:00 the next day, with a peak at 00:00. This charging pattern avoids times when electricity costs are high.

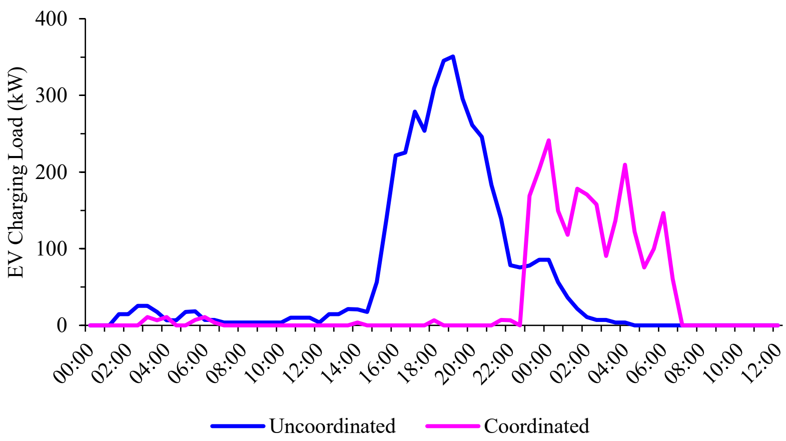

Fig. 8. EV charging profile

Two different load profiles are produced because of the different charging patterns in the two simulated scenarios. Fig. 9 compares the base load profile (no EVs) to the load profiles in both scenarios. There is a significant increase in load in the Uncoordinated scenario during peak load hours, between 17:00 and 22:00. The peak load, which was originally 5946.7 kW, increased by 5.2% to 6255.9 kW. This is because EV charging peaks coincide with peak load. The load profile, on the other hand, changes differently in the Coordinated scenario. There is no increase in load during peak load times. This occurs because EVs that arrived home is not immediately charged. However, the change in the load profile occurs between 23:00 and 05:00 because the charging load of EVs is shifted. Furthermore, the load factor of the base load, Uncoordinated, and Coordinated scenarios are 79.3%, 76.2%, and 79.7%, respectively. This demonstrates how the Coordinated scenario improves the system’s load factor.

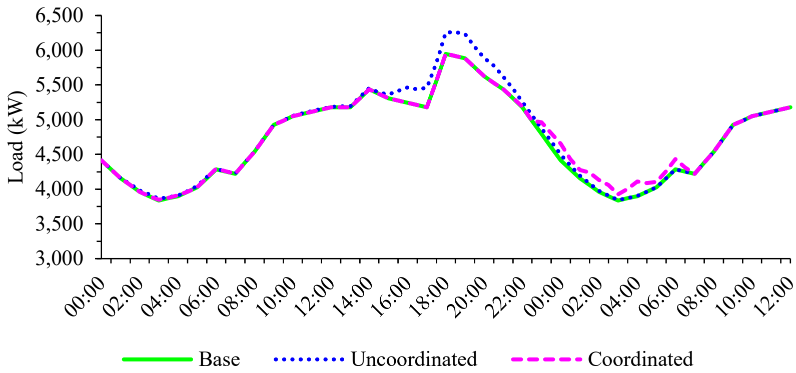

Fig. 9. Change in the load profile

3.2. EV Charging Characteristics

The SoC obtained in the two scenarios differs due to the different charging methods. For example, Fig. 10 depicts the SoC of EV no. 62 throughout the charging process. In the Uncoordinated scenario, when the EV arrives home at 18:00, the EV is immediately charged nonstop until it is nearly full at 20:00. In Coordinated charging, the charging is not started directly when the EV gets home. Furthermore, the charging process is rather irregular. Nevertheless, the EV can reach the target SoC at 07:00 the next day, three hours before the EV is used. Fig. 10 depicts the final SoC in both scenarios. Because no SoC target is set in the Uncoordinated scenario, the electric vehicle will be charged until the SoC is close to 100%. The Uncoordinated charging method yields a 96% average final SoC. Meanwhile, in the Coordinated scenario, the final SoC is expected to be 90%. The average SoC obtained is slightly less than the target of 86%. Distribution of final SoC shown in Fig. 11.

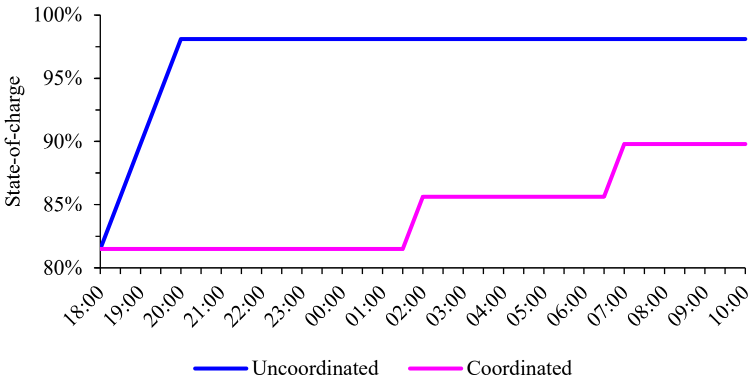

Fig. 10. SoC of EV no. 62

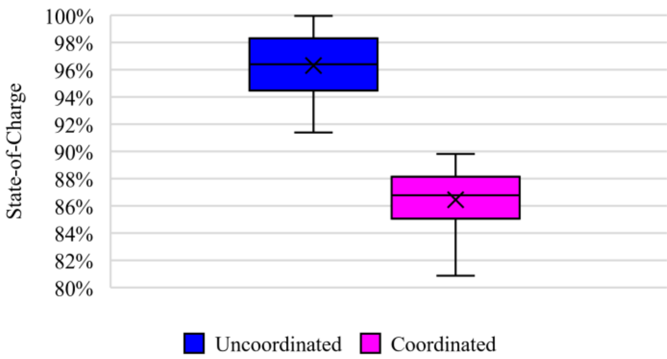

Fig. 11. Distribution of final SoC

3.3. Impact on System Power Flow

Fig. 12 and Fig. 13 show the results of the power flow simulation, i.e., transformer loading profile and bus voltage profile, respectively. There is a 12.5% loading peak in the transformer loading in the Uncoordinated scenario at 18:00. The loading value is still less than the 80% permissible loading standard. The peak loading in the Coordinated scenario, on the other hand, is still lower, at 12%. The difference in transformer loading between the two scenarios is due to the large capacity of the distribution transformer used, which is 60 MVA. As a result, there is no significant increase in load at the penetration level under consideration.

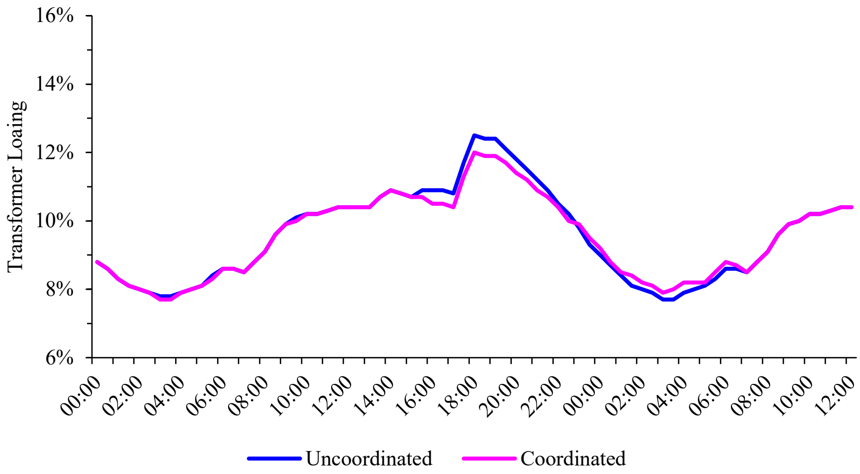

Fig. 12. Transformer loading profile

When the load demand is high, during peak load times, the bus voltage in the distribution system will generally decrease. However, the voltage of Bus 35 remains within the standard range in both the Uncoordinated and Coordinated scenarios, with no significant difference between the two, or 0.1% to be precise. Nevertheless, the voltage in the Uncoordinated scenario is generally lower during the peak load period.

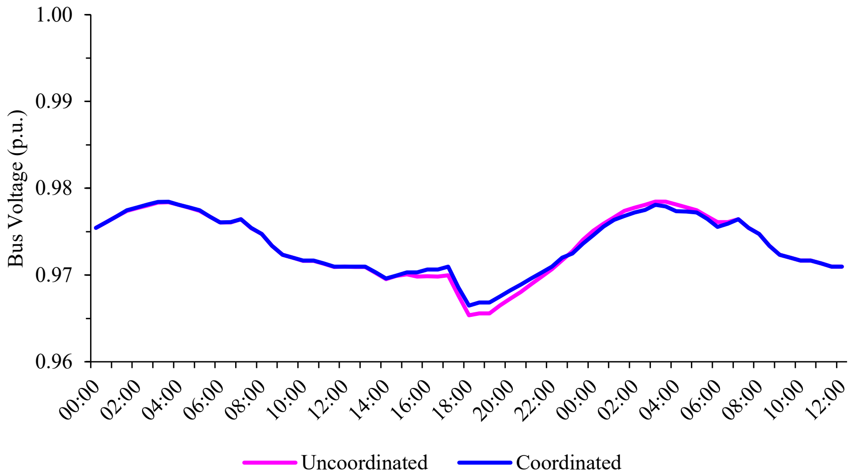

Fig. 13. Voltage profile of Bus 35

3.4. Impact on Charging Cost

Economically, the two EV charging scenarios result in different costs. Table 5 summarizes the charging costs and differences in both scenarios. The Uncoordinated charging method requires Rp3.20 million of charging cost for 150 EVs, or about Rp21,319 per EV. Meanwhile, the Coordinated charging method is much less expensive, costing only 1.37 million, or around Rp9110 per EV. That is, charging with the Coordinated method saves 57.3% of the cost than charging with the Uncoordinated method. Low charging costs can be obtained in the Coordinated scenario because EV charging takes into account changing electricity costs over time. To lower the cost, most charging is done when electricity rates are low.

Table 5. EV charging costs in both scenarios

Scenario	Total Charging Cost (Million Rp)	Average Charging Cost (Rp/EV)
Uncoordinated	3.20	21,319
Coordinated	1.37	9110
Difference	1.83	12,209

3.5. Study Comparison with Previous Works

This section compares the findings of various studies on the optimal charging schedule for electric vehicles. Table 6 compares the findings of this study to those of previous studies.

Kanchev *et al*. [22] scheduled EV charging using discrete optimization. However, this study does not go into detail about the case studies used, the electricity tariff model, or the cost of charging EVs. There was also no scheduling validation for the distribution system discovered.

Suyono *et al*. [25] optimized EV scheduling using two optimization methods, binary particle swarm optimization (BPSO) and binary grey wolf optimization (BGWO). Using the ToU tariff, coordinated charging is found to reduce charging costs by 5.45-15.89%, depending on the level of EV penetration. Afterward, the scheduling results are evaluated by simulating them to determine bus voltages and power losses in the IEEE 31 bus system.

Visakh *et al*. [21] used convex optimization to model optimal EV charging scheduling. Using dynamic pricing rates, resulted in a 30% reduction in charging costs. Simulation on the IEEE 4-node test feeder was done to validate the scheduling results and determine the impact on transformer loading and bus voltage.

In contrast to previous research, this study optimizes the scheduling of EV charging models using MILP. Furthermore, previous research only used test cases as a simulation system. As a result, a real distribution system was used in this study, along with real vehicle usage behavior data.

Table 6. Comparison of our study with previous works

Author	Optimization Method	Real Study Case	Electricity Tariff Model	Charging Cost Reduction	Power Flow Validation
Kanchev *et al.* (2018) [22]	Discrete optimization	No	Not specified	Not evaluated	Not evaluated
Suyono *et al.* (2019) [25]	BPSO and BGWO	No	ToU	5.45-15.89%	Bus voltage and power losses
Visakh *et al.* (2021) [21]	Convex optimization	No	Dynamic pricing	30%	Transformer loading and bus voltage
Our study	MILP	Yes	ToU	57.3%	Transformer loading and bus voltage

It should be noted that each study's optimal scheduling results were obtained using different optimization methods, data, and validation models. As a result, **Table 6** cannot be used to demonstrate the effectiveness of the presented optimization model unequivocally, but only for general comparisons with previous studies.

4. CONCLUSION

The optimal scheduling of EV charging was obtained in this study and tested on the Bantul 05 Feeder system. Based on the two charging scenarios that were tested, Uncoordinated and Coordinated, it is clear that Coordinated charging has several advantages over Uncoordinated charging. First, the Coordinated charging method significantly reduces EV charging costs by up to 57.3% as compared to the Uncoordinated method. Low charging costs can be obtained in the Coordinated scenario because EV charging takes into account changing electricity costs over time. To lower the cost, most charging is done when electricity rates are low. Second, by not increasing the system's peak load, the Coordinated charging reduces the distribution system transformer loading by 0.5%. The voltage profile during peak load conditions is also found to be 0.1% higher, slightly better than the Uncoordinated scenario. This demonstrates that coordinated EV charging benefits not only the EV users but also the distribution system operator by preventing system operation issues.

In this research, the electric vehicle charging station is assumed to take place entirely in the homes of EV owners. Future research may include EV charging units at other locations, e.g., public charging stations or offices. Furthermore, the impact of EV penetration levels on the charging schedule and distribution system power flow can be investigated further.

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REFERENCES

[1] G. Xu, H. Yang, and P. Schwarz, "A strengthened relationship between electricity and economic growth in China: An empirical study with a structural equation model," *Energy*, vol. 241, p. 122905, 2022, https://doi.org/10.1016/j.energy.2021.122905.

[2] R. Shankar and S. Singh, "Development of smart grid for the power sector in India," *Cleaner Energy Systems*, vol. 2, p. 100011, 2022, https://doi.org/10.1016/j.energy.2021.122905.

[3] SmartGrids European Technology Platform, Strategic deployment document for europe's electricity networks of the future," 2008. http://kigeit.org.pl/FTP/PRCIP/Literatura/020_SmartGrids_ETP_SDD_FINAL_APRIL2010.pdf (accessed Nov. 30, 2022).

[4] M. Yuan, J. Z. Thellufsen, H. Lund, and Y. Liang, "The electrification of transportation in energy transition," *Energy*, vol. 236, 2021, https://doi.org/10.1016/j.energy.2021.121564.

[5] F. Salah, J. P. Ilg, C. M. Flath, H. Basse, and C. van Dinther, "Impact of electric vehicles on distribution substations: A Swiss case study," *Appl Energy*, vol. 137, pp. 88–96, 2015, https://doi.org/10.1016/j.apenergy.2014.09.091.

[6] P. Suttakul, W. Wongsapai, T. Fongsamootr, Y. Mona, and K. Poolsawat, "Total cost of ownership of internal combustion engine and electric vehicles: A real-world comparison for the case of Thailand," *Energy Reports*, vol. 8, pp. 545–553, 2022, https://doi.org/10.1016/j.egyr.2022.05.213.

[7] D. E. Horton *et al.*, "Effect of adoption of electric vehicles on public health and air pollution in China: a modelling study," *Lancet Planet Health*, vol. 5, p. S8, 2021, https://doi.org/10.1016/S2542-5196(21)00092-9.

[8] S. Pan, W. Yu, L. M. Fulton, J. Jung, Y. Choi, and H. O. Gao, "Impacts of the large-scale use of passenger electric vehicles on public health in 30 US. metropolitan areas," *Renewable and Sustainable Energy Reviews*, vol. 173, p. 113100, 2023, https://doi.org/10.1016/j.rser.2022.113100.

[9] S. Deb, K. Kalita, and P. Mahanta, "Review of impact of electric vehicle charging station on the power grid," in *Proceedings of 2017 IEEE International Conference on Technological Advancements in Power and Energy: Exploring Energy Solutions for an Intelligent Power Grid, TAP Energy 2017*, pp. 1–6, 2018, https://doi.org/10.1109/TAPENERGY.2017.8397215.

[10] E. M. Bibra *et al.*, "Global EV Outlook 2021: Accelerating Ambitions Despite the Pandemic," 2021. https://iea.blob.core.windows.net/assets/ed5f4484-f556-4110-8c5c-4ede8bcba637/GlobalEVOutlook2021.pdf (accessed Nov. 30, 2022).

[11] European Comission, "A European strategy on clean and energy efficient vehicles," https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2010:0186:FIN:EN:PDF (accessed Nov. 30, 2022).

[12] Presiden Republik Indonesia, "Peraturan Presiden Nomor 55 Tahun 2019 Tentang Percepatan program Kendaraan Bermotor Listrik Berbasis Baterai (Battery Electric Vehicle) Untuk Transportasi Jalan," https://jdih.esdm.go.id/storage/document/Perpres%20Nomor%2055%20Tahun%202019.pdf (accessed Nov. 30, 2022).

[13] Y. Fan, C. Guo, P. Hou, and Z. Tang, "Impact of Electric Vehicle Charging on Power Load Based on TOU Price," *Energy Power Eng*, vol. 5, no. 4, pp. 1347–1351, 2013, https://doi.org/10.4236/epe.2013.54B255.

[14] C. B. Jones, M. Lave, W. Vining, and B. M. Garcia, "Uncontrolled electric vehicle charging impacts on distribution electric power systems with primarily residential, commercial or industrial loads," *Energies (Basel)*, vol. 14, no. 6, 2021, https://doi.org/10.3390/en14061688.

[15] P. Grahn, J. Rosenlind, P. Hilber, K. Alvehag, and L. Söder, "A method for evaluating the impact of electric vehicle charging on transformer hotspot temperature," in *IEEE PES Innovative Smart Grid Technologies Conference Europe*, pp. 1-8, 2011, https://doi.org/10.1109/ISGTEurope.2011.6162755.

[16] F. Rahimi and A. Ipakchi, "Demand response as a market resource under the smart grid paradigm," *IEEE Transactions on Smart Grid*, vol. 1, no. 1. pp. 82–88, 2010, https://doi.org/10.1109/TSG.2010.2045906.

[17] V. S. K. M. Balijepalli, V. Pradhan, S. A. Khaparde, and R. M. Shereef, "Review of demand response under smart grid paradigm," in *ISGT2011-India*, pp. 236–243, 2011, https://doi.org/10.1109/ISET-India.2011.6145388.

[18] M. R. Sarker, Y. Dvorkin, and M. A. Ortega-Vazquez, "Optimal participation of an electric vehicle aggregator in day-ahead energy and reserve markets," *IEEE Transactions on Power Systems*, vol. 31, no. 5, pp. 3506–3515, 2016, https://doi.org/10.1109/TPWRS.2015.2496551.

[19] H. Wang, K. Zeng, J. Liu, B. Du, and Y. Tang, "Power flow analysis of the economic dispatch considering the flexible EV charging," in *2020 IEEE 4th Conference on Energy Internet and Energy System Integration (EI2)*, pp. 2885–2888, 2020, https://doi.org/10.1109/EI250167.2020.9346772v.

[20] W. Jiang and Y. Zhen, "A Real-Time EV Charging Scheduling for Parking Lots with PV System and Energy Store System," *IEEE Access*, vol. 7, pp. 86184–86193, 2019, https://doi.org/10.1109/ACCESS.2019.2925559.

[21] A. Visakh and M. P. Selvan, "Charging-Cost Minimization of Electric Vehicles and its Impact on the Distribution Network," in *2021 9th IEEE International Conference on Power Systems (ICPS)*, pp. 1-5, 2021, https://doi.org/10.1109/ICPS52420.2021.9670292.

[22] H. C. Kanchev, V. A. Shterev, and N. L. Hinov, "Strategy for dispatching of multiple electric vehicles recharging in a microgrid," in *2018 IEEE XXVII International Scientific Conference Electronics-ET*, pp. 1–4, 2018, https://doi.org/10.1109/ET.2018.8549652.

[23] D. Said, S. Cherkaoui, and L. Khoukhi, "Scheduling Process for Electric Vehicle Home Charging," in *Smart Grid*, CRC Press, pp. 371–385, 2016, https://doi.org/10.1201/b19664-20.

[24] V. Grimm, G. Orlinskaya, L. Schewe, M. Schmidt, and G. Zöttl, "Optimal design of retailer-prosumer electricity tariffs using bilevel optimization," *Omega (United Kingdom)*, vol. 102, 2021, https://doi.org/10.1016/j.omega.2020.102327.

[25] H. Suyono, M. T. Rahman, H. Mokhlis, M. Othman, H. A. Illias, and H. Mohamad, "Optimal scheduling of plug-in electric vehicle charging including time-of-use tariff to minimize cost and system stress," *Energies (Basel)*, vol. 12, no. 8, 2019, https://doi.org/10.3390/en12081500.

[26] S. Shao, T. Zhang, M. Pipattanasomporn, and S. Rahman, "Impact of TOU rates on distribution load shapes in a smart grid with PHEV penetration," in *2010 IEEE PES Transmission and Distribution Conference and Exposition: Smart Solutions for a Changing World*, 2010, https://doi.org/10.1109/TDC.2010.5484336.

[27] I. Soares, M. J. Alves, and C. H. Antunes, "Designing time-of-use tariffs in electricity retail markets using a bi-level model – Estimating bounds when the lower level problem cannot be exactly solved," *Omega (United Kingdom)*, vol. 93, 2020, https://doi.org/10.1016/j.omega.2019.01.005.

[28] J. T. Putra, I. Istiqomah, R. Khomarudin, and A. Diantoro, "Pengaruh pembangkit photovoltaic sebagai distributed energy resources terhadap profil tegangan dan rugi-rugi daya pada Penyulang Bantul 05 Yogyakarta," *Tek. J. Sains dan Teknol*, vol. 15, no. 2, p. 72, 2019, https://doi.org/10.36055/tjst.v15i2.6811.

[29] DIgSILENT GmbH, "PowerFactory Application," https://www.digsilent.de/en/powerfactory.html (accessed Jan. 06, 2022).

[30] A. Setiawan, Z. Arifin, B. Sudiarto, and I. Garniwa, "Electricity Tariff Simulation on The Largest Electric Power System in Indonesia Using The Time Of Use and Critical Peak Pricing Schemes Based on Revenue Neutrality," in *2021 IEEE 4th International Conference on Power and Energy Applications, ICPEA 2021*, pp. 93–98, 2021, https://doi.org/10.1109/ICPEA52760.2021.9639304.

[31] N. Wang, H. Tian, S. Zhu, and Y. Li, "Analysis of public acceptance of electric vehicle charging scheduling based on the technology acceptance model," *Energy*, vol. 258, 2022, https://doi.org/10.1016/j.energy.2022.124804.

[32] Badan Pusat Statistik, "Statistik Komuter Jabodetabek: Hasil Survei Komuter Jabodetabek 2019," Jakarta. Accessed: Nov. 30, 2022. [Online]. Available: https://www.bps.go.id/publication/2019/12/04/eab87d14d99459f4016bb057/statistik-komuter-jabodetabek-2019.html

[33] "Electric Vehicle Database," https://ev-database.org/ (accessed Nov. 24, 2022).

[34] F. Marra, G. Y. Yang, C. Traholt, E. Larsen, C. N. Rasmussen, and S. You, "Demand profile study of battery electric vehicle under different charging options," in *IEEE Power and Energy Society General Meeting*, pp. 1-7, 2012, https://doi.org/10.1109/PESGM.2012.6345063.

[35] H. Dai, X. Zhang, X. Wei, Z. Sun, J. Wang, and F. Hu, "Cell-BMS validation with a hardware-in-the-loop simulation of lithium-ion battery cells for electric vehicles," *International Journal of Electrical Power and Energy Systems*, vol. 52, no. 1, pp. 174–184, 2013, https://doi.org/10.1016/j.ijepes.2013.03.037.

[36] E. Wikner and T. Thiringer, "Extending battery lifetime by avoiding high SOC," *Applied Sciences (Switzerland)*, vol. 8, no. 10, 2018, https://doi.org/10.3390/app8101825.

[37] S. Satarworn and N. Hoonchareon, "Impact of EV Home Charger on Distribution Transformer Overloading in an Urban Area," in *2017 14th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)*, pp. 469–472, 2017, https://doi.org/10.1109/ECTICon.2017.8096276.

[38] A. A. N. Amrita, W. G. Ariastina, and I. B. G. Manuaba, "Study of Transformer Lifetime Due to Loading Process on 20 KV Distribution Line," *Journal of Electrical, Electronics, and Informatics*, vol. 2, no. 2, pp. 25–28, 2018, https://doi.org/10.24843/JEEI.2018.v02.i02.p01.

[39] P. K. Roy and D. Mandal, "Quasi-oppositional biogeography-based optimization for multi-objective optimal power flow," *Electric Power Components and Systems*, vol. 40, no. 2, pp. 236–256, 2011, https://doi.org/10.1080/15325008.2011.629337.

[40] A. F. Attia, R. A. el Sehiemy, and H. M. Hasanien, "Optimal power flow solution in power systems using a novel Sine-Cosine algorithm," *International Journal of Electrical Power and Energy Systems*, vol. 99, pp. 331–343, 2018, https://doi.org/10.1016/j.ijepes.2018.01.024.

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