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AIR CONDITIONING LOAD CONTROL BASED ON THE NETWORK COST AND ELECTRICITY MARKET PRICE UNDER DEMAND SIDE RESPONSE MODEL

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Abstract. *Air conditioning (AC) is faced with a big problem to supply electricity demand and increased electricity prices to the consumer. This paper presents a new model development of demand side response (DSR) to assist small consumers particularly to optimize energy costs. The innovation of this paper is to assist small consumers to minimize energy costs. In this simulation, the consumer should undertake a pre-cooling mechanism to minimize the energy costs by anticipating the expensive cost. This model is applicable for residential homes in Makassar, South Sulawesi Indonesia. The results indicated the potential benefit of DSR to achieve energy saving for both consumers and aggregators.*

Keywords: Demand side response, Energy cost, Minimize, Pre-cooling, Small consumer

1. **Introduction.** According to the history of the peak load each day, peak sessions usually occur in the middle of the day and in the afternoon. Due to extreme temperatures around midday, all consumers applied AC at the same time, resulting in an increase in peak demand. In addition, peak demand mostly occurs when consumers begin using their appliances such as washing machines, televisions, ovens, computers and dishwashers at the same time.

Energy use in the cooling sector has been growing rapidly. In 2015, ACs load contributed around 20 per cent of electricity demand in 150 developing countries. The authors in [1] argue that in the next 15 years, the number of room ACs will increase to 1.5 billion. The ACs create a substantial portion of residential energy demand, particularly in tropical regions. Therefore, more than 40 countries in the world have realized some regulations to manage demand for AC.

The effects of residential AC on peak demand are great potential against availability of electricity supply and seasonal peak prices. Many consumers and utilities have identified the enormous challenges of increasing peak demand due to the load of AC [2]. They are promoting and conducting joint research with some researchers and academics to address the peak demand problems, for example: shaving or shifting the peak demand [3-5], curtailing energy use [6,7], directing load control [8-12], building thermal performance [13-15], demanding response program [16-19].

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The rapid economic and population growth has significantly affected the growth in electricity demand in both the commercial and residential sectors. Continuous efforts to establish new buildings with inefficient maintenance especially on AC equipment will increase energy requirements. To meet peak demand, one kW of AC installed in residential homes are more expensive in new energy infrastructure and these costs are shared by all users. Peak demand is a major factor in increasing electricity prices. Electricity peak demand usually occurs if the level of electricity is the maximum supplied to the power network. In Makassar, electricity peak demand/load normally appears on days with high temperatures or hot summers. The increase of demand is due to the broad use of AC. It means that an electricity price spike will be generated on days with hot temperatures. As ambient temperatures move up, price spikes often happen during the day, consequently increasing the utilization of ACs. In tandem with energy markets, the costs increase, as many ACs operate at the same time.

To address the above problem, an innovative model of DSR is developed in this paper. The simplified process is: an optimization model is formulated to minimize energy costs according to the electricity market price (EMP) and network cost (NC). Due to the extreme climate temperature an electricity price spike was experienced during hot days. To justify this model, total cost (TC) is calculated considering the probability of a price spike (Pr) and outside temperature (T_o). The main contributions of this paper are highlighted below:

1) DSR models for small consumers to control the AC loads and price based on the NC cost and EMP are designed. This method was applied to minimize the energy costs for the ACs considering the T_o and Pr.
2) This work will assist consumers to reach financial joint profits for both small consumers and aggregators.
3) In addition, this research examined how the pre-cooling strategy can be applied by consumers to minimize energy costs for the ACs.

In this paper, building characteristics for residential houses in Makassar and EMP released by the Indonesia electricity state company (called PLN) are chosen for the case studies. This paper is systematized in five sections. Section 1 is introduction; Section 2 is the literature review; Section 3 is model description; Section 4 is result of optimization and analysis; Section 5 is conclusion.

2. **Literature Review.**

2.1. **Demand side response.**

DSR can be defined as an effective way to reduce the electricity generation price and minimize electricity bills for the consumer [20-22]. DSR can be simply defined as the change electricity usage based on the signal price/load from electricity provider [23]. DSR is a new intelligent method to reduce the electricity loads/price from peak to off-peak seasons or to shift consumer electricity consumption [24-26]. As a result, it can increase the reliability and efficiency as well as to provide benefits for the power utilities and consumers [27,28]. Furthermore, DSR programs are not just to provide a program for consumers but also to enable the reduction of the power consumption and it has potential to save energy [29-31], maintain the distribution system infrastructure, and can be used to reduce peak electricity demand [26,32].

According to [33] DSR program assists for small consumers to decrease or to reallocate their electricity use in the peak season. DSR is an alternative solution for motivating the consumers to minimize or reduce their demand during peak season with an incentive rate [34]. Under the DSR program, small consumers can manage their demand for power consumption. DSR is a practical established solution and effective for energy management

[35]. It was developed for smart homes and has helped to mitigate peak power demand [35,36].

Some literature reported that several efforts and innovative research have been undertaken by governments and utilities to mitigate peak electricity demands under a demand response program; for example, electricity reform price in China [37]; impact on demand response loads program in Korea [38]; a new framework of demand response for electricity retailers in Australia [39]; electricity demand response mechanisms for small consumers in Europe [40]; the potential of demand response to increase profits for chemical industry [41]. However, none of these methods mentioned above had been applied for the ACs and the same potential level of reduction energy costs, as illustrated in this paper.

In addition, studies of the DSR model to reduce peak demand for ACs have primarily focused on building [42,43] applying simulation to optimizing the operation of ACs [44,45]. The authors in [46,47] demonstrated that DSR program and genetic algorithm is applied to reduce the wholesale electricity costs and peak demand. Consequently, the DSR program can reduce peak demand around 9% [48]. While a study by [11] demonstrated power reduction perhaps 23% under the DSR program. In the proposed method suggested that additional strategies to reduce peak demand and can keep room temperature comfortable for the consumer, such as a pre-cooling method.

2.2. **Small consumers and the aggregators.** The aggregator has emerged as a way to resolve the disparity in benefits between utilities and according to electricity market regulation, small consumers are not permitted direct participation in the wholesale EMP, only a big consumer can offer to bid, curtail, shift to wholesale EMP and demand. Therefore, small consumers are required to join with the aggregator.

The aggregator has appeared to avoid the gap between electricity provider and consumer side. Under DSR program aggregator is a communicator between electricity providers and small consumers [49]. The aggregator negotiates the electricity price with the utility located within their group according to the geographical area, such as suburb and street; or institutional user, such as university or school. Aggregators are a group which gather users together to be served through a competitive electricity provider [50].

The authors in [51] argue that an aggregator joins a minimum or more than two consumers to negotiate the EMP and NC from retail electric providers (REPs). An aggregator is an organization or small group that brings retail electricity consumers collected with the aim to receive good service, provide flexibility and competitive prices and provide a valuable service [52,53].

Under the DSR program, the aggregator provides information about the electricity price for day-ahead and demand. To achieve the minimum cost, optimize scheduling to turn-on and turn-off the AC using the best response technique. In this model, energy costs for every consumer are based on day-ahead of the energy usage of other consumers and outdoor temperature profile. To manage energy consumption of each consumer is based on the information about the energy consumption schedule. Therefore, communication both consumers and electricity providers are compulsory to get schedule of energy consumption. The electricity provider is required to share information regarding electricity prices and temperatures. Consequently, the consumer can manage the time to use the AC. In addition, a pre-cooling scheme was applied to anticipate the high cost [54,55] and the aggregator is needed to communicate information to both consumer and utility/electricity provider [45,56].

3. **Model Description.** In this research, optimized the energy cost for the AC considering the EMP and network overload was applied to determine the minimum cost. Based

on the duration of the spike, there were some cases of a price spike occurring on hot days, namely: half an hour (0.5 h), one hour (1 h), and one and a half hours (1.5 h) spike. However, in this research we only analysed combined cases with a price spike which may happen during any five minutes intervals during the day. Due to the significant probability, price spikes of two hours and more were not considered. In addition, the T_o data on 14 July 2019 was chosen for the case study.

To compute the energy cost, there are 40 switched edges decided which satisfy the constraint to find the minimum cost. In this research, numerical optimization (coded algorithms) under MATLAB was applied to calculate total cost (TC) considering the EMP and network overload.

In this optimization process, the minimum permitted temperature was 21°C. In contrast, the maximum permitted temperature was 25°C. The AC was operated between 10:00 AM and 19:00 PM in consideration of the probability of a price spike. To avoid expensive costs, a pre-cooling method was necessary to apply [57]. Pre-cooling method set up the room temperature to be lower than usual [48]. Some strategies of pre-cooling have been applied and developed in [58-62]. In this research, a pre-cooling method was applied only when there was a substantial electricity price in hot climates.

3.1. **The characteristic of the room.** The characteristic of the room and AC applied in this research are shown in Table 1 below.

Table 1. Some parameters used in this research

No.	Parameter	Value	Unit
1	Heat transfer coefficient	1.2	W/m^2°C
2	Total area	15	m^2
3	Heat capacity of the room	20	J/°C
4	Heat transfer from the AC	900	W
5	Maximum temperature	25	°C
6	Minimum temperature	19	°C
7	Rating power of AC	2.6	kW
8	Number of switch change events	40	

Based on the historical analysis data, a lower threshold value of 1064.023 IDR/kWh was applied to examine the EMP. This means that a price spike recognizes if any price is more than 1064.023 IDR/kWh. In contrast, regular price (no-spike price) was the average of electricity price under 1064.023 IDR/kWh, in this case 532.115 IDR/kWh. In addition, a lower threshold value of 500000 kW was applied to analyse network overload. This means that network overload recognizes when demand is more than 500000 kW. In this optimization, a tariff network component of 2500 IDR/kWh and 25000 IDR/kWh were applied for the normal price and full price.

3.2. **Peak demand based on the NC.** On hot days many users operated their AC at the same time. Based on the historical temperature data, all users operated the AC usually in the middle of the day. Due to the extreme temperature, network overload was recorded from 13:00 PM to 14:30 PM on weekdays.

In the optimization process, the network overload price (called penalties) was recognized when the value of demand (D) was more than the rating of the transformer (Dr). There are several options for consumers as an indicator to restrict demand when the feeder is overloaded. For example, brick wall penalty and linear penalty. Due to easy

implementation, a brick wall penalty was used in this simulation. A brick wall penalty is applied when the NC suddenly increased as the loading exceeded the rating of distribution transformer. The problem with this method is that consumers still incur a big penalty even when the overload is only small.

The following Equation (1) is used to compute the NC. The network overload price (N_1) is the penalty price, N_2 is normal price, S is rating power of AC (kW), P is electricity price (IDR/kWh).

$$NC(t) = \int_{t=1}^{t=n} [(S(t) \cdot P(t) \cdot X(t) \cdot Y(t))dt + K] \tag{1}$$

subject to constraint:

$$\begin{aligned} &\text{If } D > Dr \\ &\qquad S(t) = N_1 \\ &\text{Else } S(t) = N_2 \end{aligned} \tag{2}$$

The NC was calculated according to the AC status. The NC was increased if the temperature was being decreased by turning on the AC. Nevertheless, there was no NC if the AC status was off.

3.3. **Peak demand considering NC and the EMP.** In this simulation, a finite probability every five minutes of a price spike was considered to define the total cost. P_s is electricity price when spike occurs and P_n as the electricity price when no spike occurs. MC_n and MC_s are the market cost without the spike and market cost when a spike happens. MC_{30}, MC_{60} and MC_{90} are market cost for 0.5 h spike, 1 h spike and 1.5 h spike, respectively. If considering the probability of a price spike, then: Pr_{30i} is probability of a price spike for 0.5 h, Pr_{60i} for 1 h and Pr_{90i} for 1.5 h spike. Consequently, the following equation is used to determine total market cost (TMC):

$$\begin{aligned} TMC(t) = &\sum_{i=1}^{n} [MC_{30i}(t) * Pr_{30i}(t) + MC_{60i}(t) * Pr_{60i}(t) + MC_{90i}(t) * Pr_{90i}(t)] \\ &+ MC_n(t) * \prod_{i=1}^{n} (1 - Pr_{30i}(t) - Pr_{60i}(t) - Pr_{90i}(t)) \end{aligned} \tag{3}$$

subject to constraints:

$$MC_s(t) = \int_{t=1}^{t=n} [(S_s(t) \cdot P_s(t) \cdot X'_s(t) \cdot Y(t))\, dt + K] \tag{4}$$

$$MC_n(t) = \int_{t=1}^{t=n} [(S_n(t) \cdot P_n(t) \cdot X(t) \cdot Y(t))\, dt + K] \tag{5}$$

$$S_s(t) = \frac{S_{\max} * (T_o(t) - T_l(t))}{(T_o(t) - T_{\min})} \tag{6}$$

$$S_n(t) = \frac{S_{\max} * (T_o(t) - T_{\max}(t))}{(T_o(t) - T_{\min})} \tag{7}$$

where, X is the duration of the spike (hour); Y is binary variable (0 or 1); K is penalty; T_l, $T_{\max}$ and $T_{\min}$ are low temperature (°C), maximum temperature (°C) and minimum temperature (°C); S_s, S_n and $S_{\max}$ are rating power when a spike occurs, no spike happens and rating power maximum (kW).

Consequently, the following equation is used to calculate the total cost (TC):

$$TC(t) = NC(t) + TMC(t) \tag{8}$$

Collective benefit could be earned by consumers when the consumer applies a DSR program. The following Equation (9) is used to calculate collective benefit (CB). If TC_o is the total cost without a DSR and TC is the total cost under a DSR program, then CB is expressed by:

$$CB = TC_o - TC \tag{9}$$

The following equation is to determine the percentage of collective benefit (%CB):

$$\%CB = \frac{CB(\$)}{TC_o(\$)} \tag{10}$$

4. **Result of Optimization and Analysis.** In this research, the NC and market price were applied to analyze data and compute the numerical result released on the PLN during hot days from 1st January 2016 to the 31st July 2019.

4.1. **Case 1: Total cost without DSR program.** In this simulation, consumers operated the AC between minimum and maximum permitted temperatures. The control system turned on the AC if the room temperature rose to the upper temperature. In contrast, the control system switched off the AC when the temperature decreased to the lower temperature. The operation of the AC was continuous time without considering the network overload.

Equations (1) to (7) above were applied to calculate the results of optimization, as shown in Figures 1 and 2, Table 2.

The following Figure 1 illustrated the kind operation of the AC when consumer did not apply the DSR program.

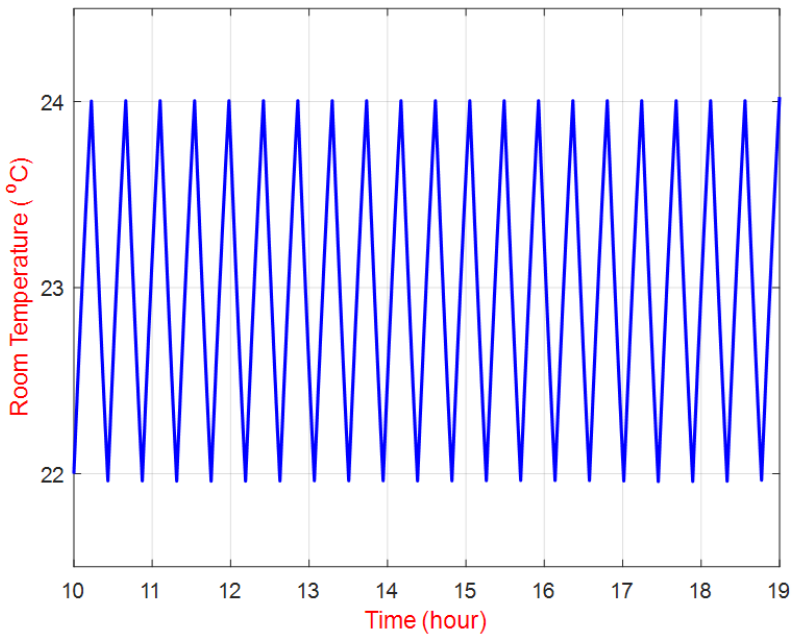

FIGURE 1. Controlling temperature without DSR program

Figure 1 illustrates how the control system sets the inside room temperature. In this simulation, temperatures of 24°C and 22°C were chosen as selected maximum and minimum. Temperature of 22°C was chosen for the starting point while the AC status was off. In this simulation, the substantial risk of the market price and network overload did not consider cycling temperature. This means the pre-cooling strategy was not necessary to apply in this simulation. As a result, the consumer paid an expensive cost.

Figure 2 below illustrates the total NC and market cost considering the probability of a price spike. Due to the temperature not being controlled under the DSR program, then the total market costs without DSR (TMC_o) and NC without DSR (NC_o) were expensive, as given in Table 2.

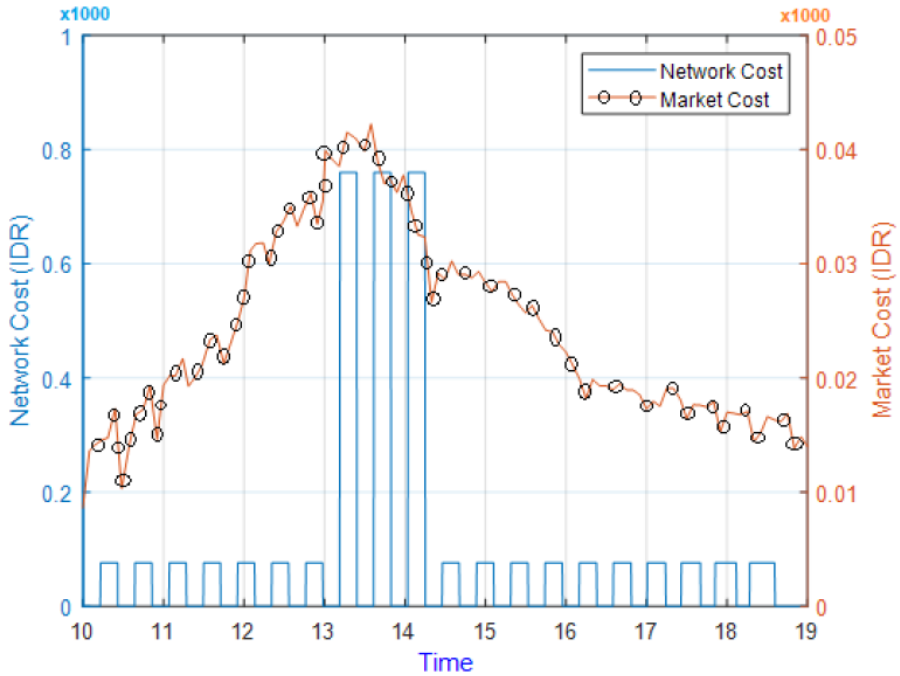

FIGURE 2. Total network and market cost without DSR program

TABLE 2. Total cost without DSR program

TC_o (IDR)	NC_o (IDR)	TMC_o (IDR)
22695	1636	6335

4.2. **Case 2: Total cost under DSR program.** Similar to the previous scheme, the control system maintains the inside room temperature from lower to upper temperature. In this research, the selected minimum and maximum temperatures were 21°C and 25°C with starting point temperature of 21°C.

To compute the total cost, the electricity cost was increased when the AC status was ON. In contrast, there was no cost if the AC status was OFF. In addition, the electricity cost calculation included the NC.

The following Figure 3 indicates the result of optimization under the DSR program. In this simulation, the cycling temperature considers the substantial risk of the market price and network overload. This means that a pre-cooling strategy was compulsory to avoid an expensive cost during these periods.

Equations (1) to (7) were applied to calculate the numerical results of optimisation of the AC, as shown in Figures 3 to 4 and Table 3.

Figure 4 illustrates the network and market cost under DSR program. The NC was increased because peak demand occurred from 13:00 PM to 14:30 PM. However, under the DSR program the AC status was only turned on for a short time. In addition, the form of the market price was similar to the form of the Pr and T_o. Consequently, total cost is affected by the Pr and T_o. In this simulation, the resulting cost was quite high

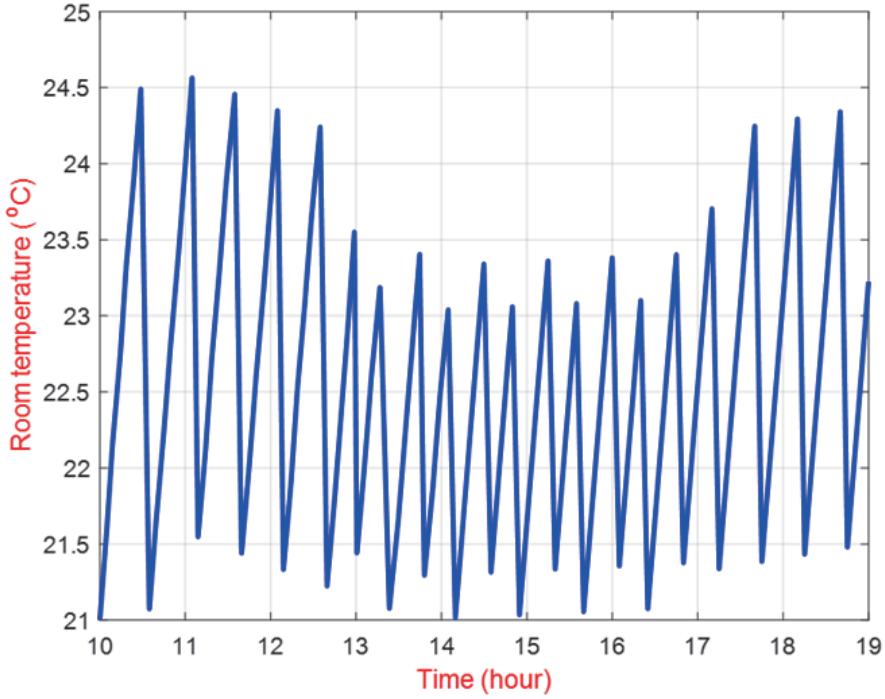

FIGURE 3. Room temperature under DSR program

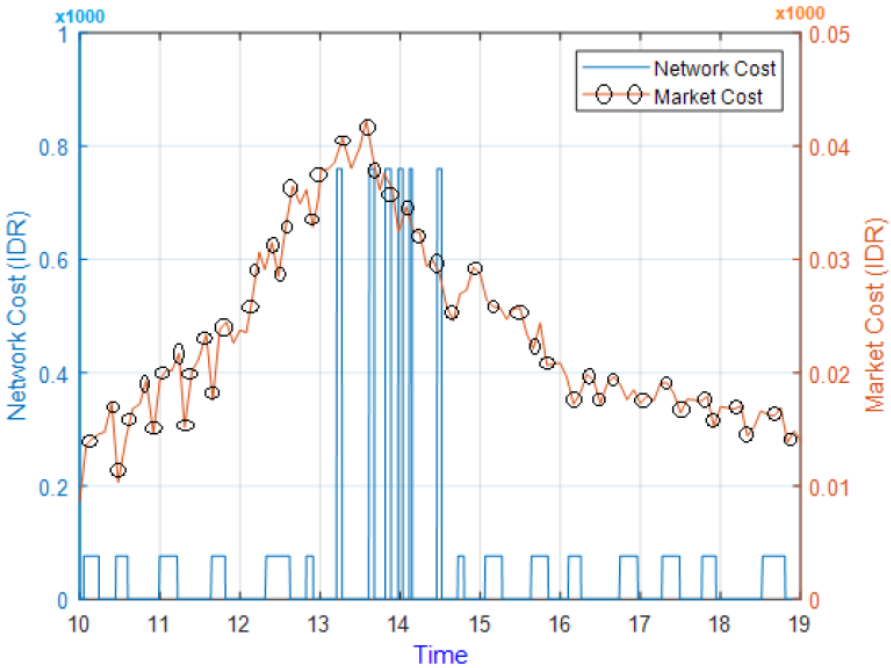

FIGURE 4. Network and market cost under DSR program

because the network overload occurred from 13:00 PM to 14:30 PM. Equations (3) to (8) were applied to calculate the market cost, as shown in Figure 4 and Table 3.

Equations (9) and (10) were applied to compute the CB, as given in Table 4.

Table 4 illustrates how consumers earn collective benefit if applying the DSR program. The consumer could minimize the energy cost for operating the AC to meet peak demand. According to the characteristics of the room and the AC, the CB for the consumer was

Table 3. TC under DSR program

TC (IDR)	NC_o (IDR)	TMC_o (IDR)
14801	8382	6419

Table 4. Collective benefit

Number of Consumers	Total Cost			
	Without DSR TC_o (IDR)	Under DSR TC (IDR)	Collective Benefit (CB)	
			(IDR)	(%)
Consumer-1	22695	14801	7894	34.78

IDR 7894 (34.78%). This illustrated that the pre-cooling strategy was needed and an effective way to reduce the energy costs.

4.3. **Case 3: Benefits of DSR program for several consumers.** In this segment benefits of the DSR program for several consumers with different varying typical rooms (k1) were discussed. In this simulation, the number of switching for every selected k1 was based on the physical characteristics of the room. The selected temperatures without the DSR program were from 22°C to 24°C for the all selected k1 and 21°C to 25°C under the DSR program. The following Table 5 illustrates the selected k1 according to the number of switching events.

Table 5. k1 according to number of switching

Number of Consumer	Number of Switching	k1
Consumer-1	40	1.20
Consumer-2	44	1.25
Consumer-3	48	1.30
Consumer-4	52	1.35

According to [63] k1 is small when the room is large and well-insulated, then it loses or gains heat slowly. In contrast, k1 is large when the room is small and poorly-insulated, then it loses or gains heat more quickly. Therefore, the number of k1 depends on the physical characteristics of the room.

The result of cycling temperature without the DSR program according to the selected k1 is illustrated in the following Figure 5.

Figure 5 illustrates the normalisation of the room temperature between 24°C and 22°C were selected for without the DSR program. The temperature only cycled from the maximum to minimum without considering the significant risk of the network overload and EMP. In this simulation, the setting of selected k1 and number of switching is only to compare the cycling room temperature. For example: k1 was 1.20 for 40 number of switching, k1 was 1.25 for 44 number of switching, k1 was 1.30 for 48 number of switching and k1 was 1.35 for 52 number of switching.

Figure 6 indicates the cycling temperature under the DSR program. According to the k1 and number of switching events, the cycling temperature was optimised to determine the minimum cost and comfortable room temperature. Due to the substantial risk of the EMP and network overload that a pre-cooling method was needed to be applied during these periods. The cycling temperature decreased to a lower temperature when the T_o and Pr were increased, as indicated in Figure 6.

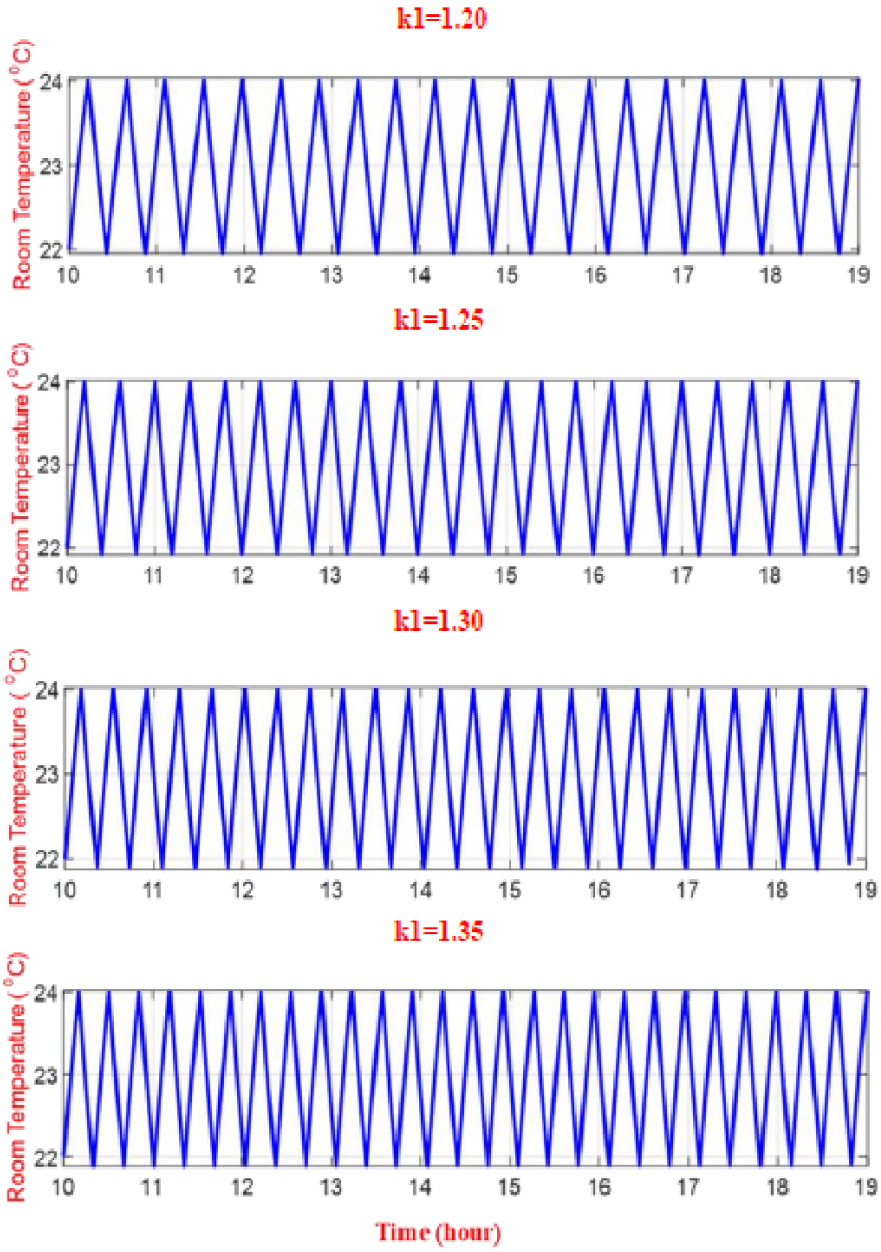

FIGURE 5. Room temperature without DSR program

To keep a comfortable room temperature for the consumer, under the DSR program that the cycling upper and lower temperatures were 25°C and 21°C. This was to give more optimum choices and flexibility. These figures illustrate the room temperature decreased to a lower level from 12:30 PM to 17:00 PM. This is because of the substantial risk of the market price during these periods.

Equations (9) and (10) were applied to determine the CB for the consumer. Table 6 illustrates the CB according to the k1 of the room. There is a strong relationship between total cost without and under DSR and CB for every consumer. The highest CB was for Consumer-4 at IDR 11497 (36.65%). The second highest CB was for Consumer-3 at IDR 9812 (35.76%). The CB for Consumer-2 and Consumer-1 were IDR 8832 (34.87%) and IDR 7894 (34.78%) respectively.

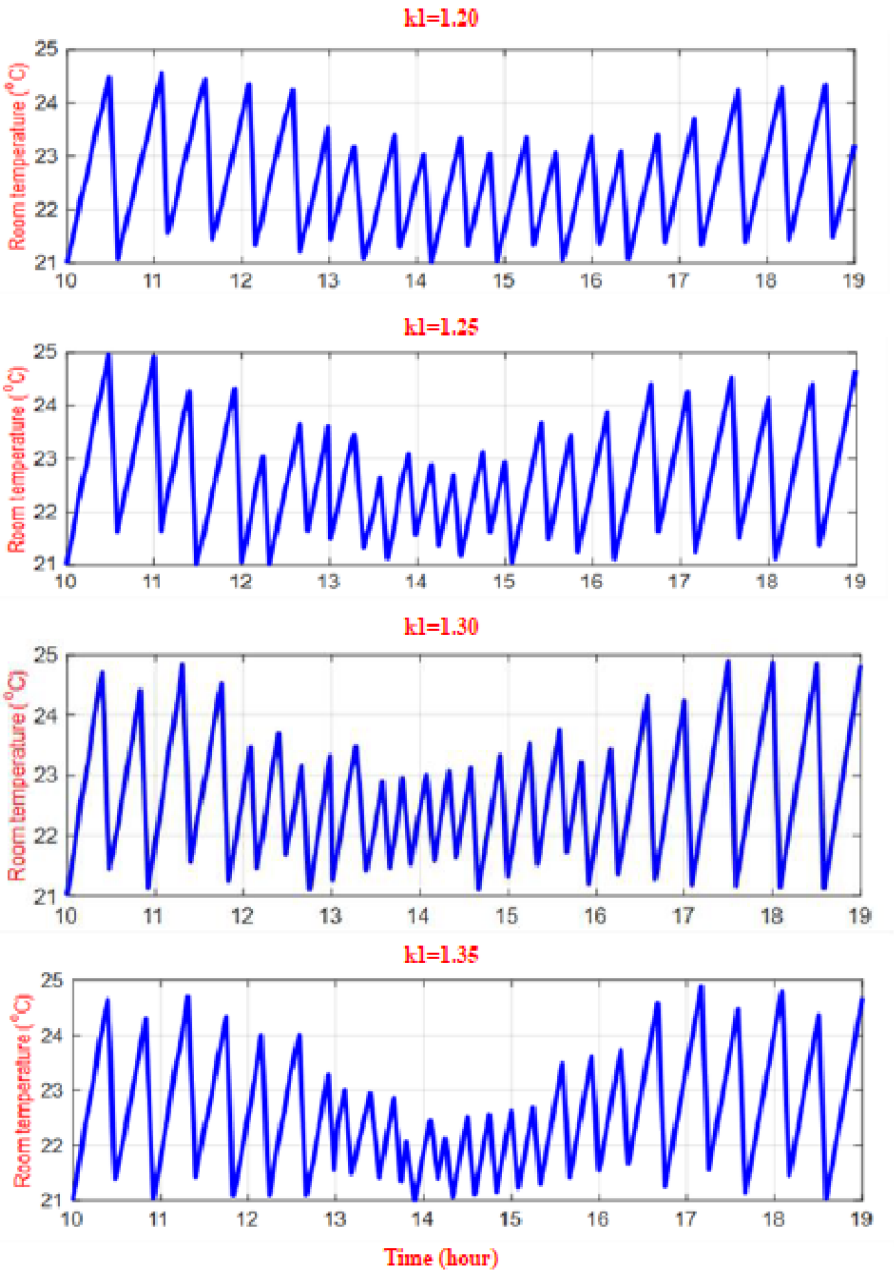

FIGURE 6. Room temperature under DSR program

TABLE 6. CB for all consumers and aggregators

Consumers	Total Cost			
	TC_o (IDR)	TC (IDR)	CB	
			(IDR)	(%)
Consumer-1	22695	14801	7894	34.78
Consumer-2	25323	16491	8832	34.87
Consumer-3	27432	17620	9812	35.76
Consumer-4	31367	19870	11497	36.65

It can be seen in Figure 7, there was a strong correlation between the CB and the value of k1. The graph illustrates that the consumer reached greatest CB when the k1 is higher. On the other hand, CB was lower when the k1 was small. This was because of leaking energy factor. A high energy cost is caused by leaking energy. Consequently, the CB of consumer-1 was smaller than others. In this simulation, the change of number k1 was necessary to determine the number of switching events the AC.

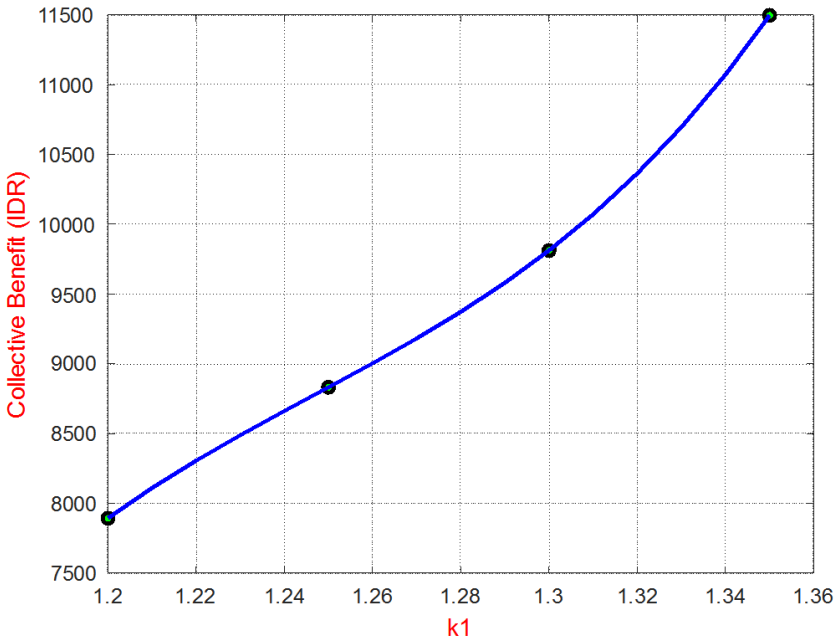

FIGURE 7. CB as a function of k1

4.4. **Case 4: The consequence of changing temperature range.** To justify this model, changing temperature range is required to define the consequence of total cost. The numerical optimization set up the time to switch on and switch off which satisfy the constraints and define minimum cost. Figure 8 illustrates the consequence of change temperature range between selecting a lower and an upper temperature. In this simulation, the minimum and maximum temperatures between 21.5°C and 24.5°C satisfy the selection of k1.

Figure 8 illustrates the control system cycle room temperature from a lower to upper selected temperature. As described in the previous method, the inside room temperature decreased to a lower level from 12:30 PM to 17:00 PM when the outside room temperature, the probability of a price spike and network overload were increased. In this simulation process, the temperature range was smaller than previous one. As a result, consumer earned different CB as the impact of a change in the temperature range.

Equations (9) and (10) were used to calculate the CB for all consumers and aggregators, as given in the following Table 7.

Table 7 illustrates the CB for all consumers according to the k1 of the room. In this scenario, the selected permitted temperature was smaller than previous one. As a result, the CB was smaller than previous one (see Table 7). The highest CB was Consumer-4 at IDR 10935 (34.86%). The second highest CB was Consumer-3 at IDR 9532 (34.75%). The CB for Consumer-2 and Consumer-1 were IDR 8774 (34.65%) and IDR 7842 (34.55%).

Figure 9 illustrates the strong correlation between the CB and number of k1. The highest CB is affected by a high k1. In contrast, due to the k1 being smaller, then the consumer

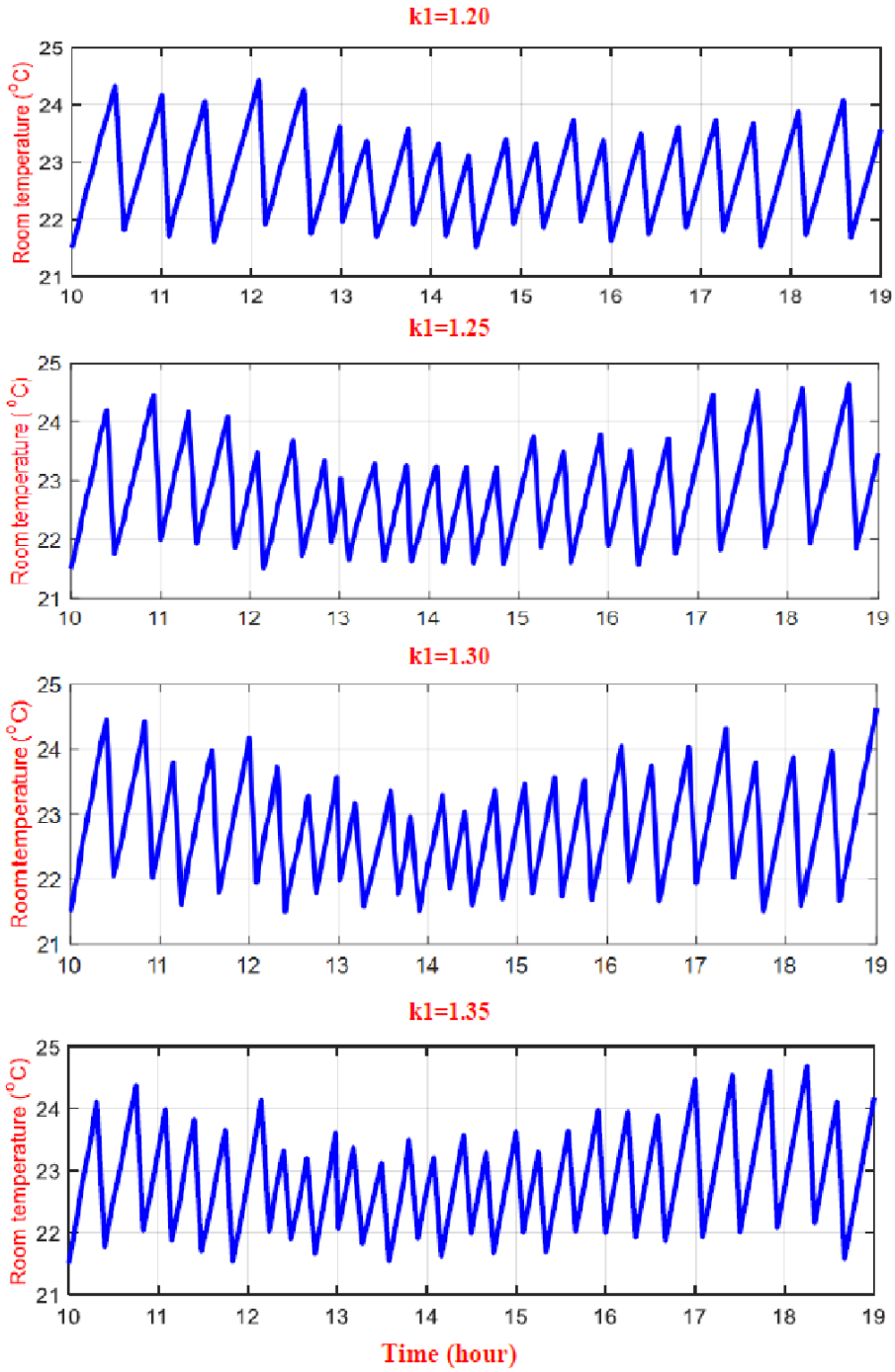

FIGURE 8. Room temperature under DSR program (case 4)

TABLE 7. CB for all consumers and aggregators (case 4)

Consumers	Total Cost			
	TC_o (IDR)	TC (IDR)	CB	
			(IDR)	(%)
Consumer-1	22695	14853	7842	34.55
Consumer-2	25323	16549	8774	34.65
Consumer-3	27432	17900	9532	34.75
Consumer-4	31367	20432	10935	34.86

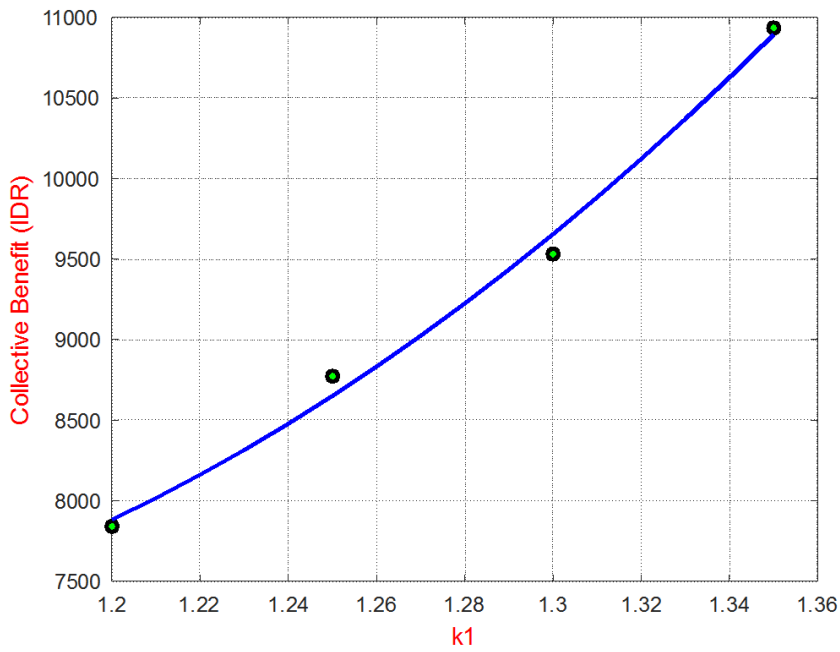

FIGURE 9. CB as a function of k1 (case 4)

earned smallest CB. Leaking energy could lead to high energy costs. Consequently, the CB for Consumer-1 was smaller than other consumers.

5. **Conclusions.** The result of optimization illustrated the pattern of control of the ACs under DSR model. In the proposed method indicated that the T_o and Pr had a significant impact to define the form of the cycle room temperature and TC. In this simulation, the resulting cost was quite high because the network overload occurred from 13:00 to 14:30. However, under the DSR program the consumer could minimize the energy costs for operating the AC to meet peak demand. While due to substantial risk of the market price from 12:30 PM to 17:00 PM then the room temperature decreased to a lower level. As a result, both small consumers and aggregators could earn CB. In this research, CB earned by consumer depended on the typical characteristics of the room. The highest CB is affected by a high value of k1. In contrast, due to the k1 being small then the consumer earned smallest CB. In addition, a pre-cooling method was applied to minimize energy costs when there is a substantial risk of the market price. This model was only appropriate according to the characteristic of room, AC and on EMP data from the PLN for hot days from 1st January 2016 to the 31st July 2019. This model is appropriate to apply if a price spike may occur during any five minutes for 0.5 h, 1 h and 1.5 h during a day and network overload just conducted within 1.5 hours between 13:00 PM to 14:30 PM.

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