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Utilizing Electricity Consumption Data to Assess the Noise Discomfort Caused by Electrical Appliances between Neighbors: A Case Study of a Campus Apartment Building

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Abstract: Real-time collection of household electricity consumption data has been facilitated by an advanced metering infrastructure. In recent studies, collected data have been processed to provide information on household appliance usage. The noise caused by electrical appliances from neighboring households constitutes a major issue, which is related to discomfort and even mental diseases. The assessment of noise discomfort using electricity consumption data has not been dealt with in the literature up to this day. In this study, a method that utilizes electricity consumption data for the assessment of noise discomfort levels caused by electrical appliances between neighboring households is proposed. This method is based on the differences in the usage time of electrical appliances in a collective residential building. The proposed method includes the following four steps: data collection and preprocessing, residential units clustering, noise discomfort modeling, and evaluation of noise discomfort. This method is demonstrated through a case study of a campus apartment building. Variations in the noise discomfort assessment model and measures for alleviating noise discomfort are also discussed. The proposed method can guide the application of electricity consumption data to the assessment and alleviation of noise discomfort from home appliances at an apartment building.

Keywords: energy data; electricity consumption data; electrical appliance noise; noise discomfort assessment; campus apartment building

1. Introduction

The recent deployment of advanced metering infrastructure (AMI) has facilitated the measurement, collection, monitoring, and sharing of data related to electrical consumption in buildings [1]. Electricity consumption data can provide information on a household's electricity consumption lifestyle, including the scale and timing of electricity consumption [2,3]. In the past, these data were utilized for the saving, efficiency, reliability, and sustainability of electricity usage. Recently, they have been widely utilized to provide information on the lifestyle and indoor comfort and to maximize environmental satisfaction [4,5].

Noise pollution caused by household appliances is a serious issue [6,7]. A substantial amount of noise is attributed to electrical appliances such as hair dryers and vacuum cleaners [8]. This noise may cause interference in speech and sleep [9] and discomfort [10], which are serious problems encountered by residents. Attempts to identify noise problems among neighboring households have been presented in many studies. Solutions to these problems through qualitative methods, such as interviews or surveys in the social science field, have also been provided. However, the extraction of accurate information on noise and its sources is difficult to achieve because the aforementioned methods depend on the ability of residents to remember specific events [11,12]. Furthermore, such methods are time-consuming and costly for the assessor and residents.

In this study, noise discomfort (ND) is defined as the discomfort caused by noise from electrical appliances between neighboring households. A method that utilizes electricity consumption data to assess the ND experienced by household residents in a collective residential building is proposed in this study. Residents regularly use electrical appliances because they live according to routine lifestyle patterns [3,13]. However, electrical appliance usages are different between households depending on various factors, such as number of members and location [14]. Sounds from electrical appliances may turn into noise, and household residents could experience discomfort when their neighbors' usage times do not coincide with their own [15]. The proposed method considers the differences in the usage time of electrical appliances to assess the discomfort caused by noise from neighboring households. Initially, electricity consumption data collected from units of an apartment building are preprocessed and formatted for residential units clustering. After the data preparation, the residential units are clustered based on the time and amount of electricity consumption, and a representative electricity consumption pattern of each group is identified. An ND assessment model is then developed. This model uses the representative patterns of groups to identify the differences in the usage time of electrical appliances between neighbors. Finally, the ND caused by neighboring households is evaluated by the proposed model.

In this paper, the application of the proposed method through a case study of a campus apartment building, which includes 75 households, at the Pohang University of Science and Technology (POSTECH), in Korea, is presented. The electricity consumption data of each unit in the apartment building were collected for four months from February 18 to June 7, 2019. According to the method, the 75 units were divided into three groups based on the time and amount of electricity consumption, and the representative electricity consumption pattern of each group was identified. An ND assessment model was then developed, and the ND caused by neighboring households was evaluated based on the differences in the usage time of electrical appliances. To highlight the practicality of the proposed method considering different cases, variations in the ND assessment model and measures for ND alleviation considering the occurrence of various events on the campus are also discussed.

The remainder of this paper is structured as follows. A review of the existing studies is presented in Section 2. The method to assess ND by utilizing electricity consumption data is introduced in Section 3. The proposed method is explained step by step through a case study in Section 4. Variations in the ND assessment model and measures for ND alleviation along with some examples are discussed in Section 5. The final remarks, contributions, and future research work are provided in Section 6.

2. Literature Review

Information on the usage time of electrical appliances can be found in the electricity consumption data. These data can be processed to provide information on usage patterns and predict their behavior [16,17]. Ref. [18] developed a procedure to identify the pattern-of-use of domestic appliances based on electricity consumption data. Ref. [19] also found patterns regarding the use of domestic appliances by processing the electricity consumption data. They proposed three electrical appliance categories and found usage trends in each category. Ref. [20] proposed a general model for the prediction of the starting time of appliances. Ref. [21] proposed a novel model to detect appliance usage events. The proposed model shows the high detection accuracy when multiple appliances are used. Ref. [22] showed that smart meter data are useful to identify appliance usage patterns. They collected electricity consumption data from 22 houses in Korea and identified when and how long occupants utilize appliances at home by analyzing the collected data. These studies demonstrated the feasibility of the usage pattern identification of electrical appliances by processing electricity consumption data.

The noise caused by electrical home appliances has been considered a serious problem [23]. Ref. [24] examined the noise originating from home appliances. They found that kitchen appliances are generally noisier than other appliances, with noise levels in the range 40–90 dB, approximately. Ref. [25] found that the noise caused by a refrigerator in a real living room is approximately 10 dB higher than the corresponding noise level measured in an anechoic chamber. Ref. [26] found that among dryers, Kimchi refrigerators, vacuum cleaners, and wind machines, Kimchi refrigerators have the highest noise roughness and fluctuation, whereas vacuum cleaners have the highest noise sharpness. Ref. [27] indicates that the most common air transmitted noise between neighbors is generated by household appliances, according to a survey with 137,813 telephone consultations from 2012 to 2018, in Korea.

Residents may feel ND due to the differences in the usage times of electrical appliances by neighboring households. Ref. [15] claimed that large differences in the usage time of electrical appliances between neighboring households increase ND. Ref. [28] also contended that households with distinct cultures have different living behavior patterns and appliance usage; these differences cause ND. For example, the residents of a household who usually sleep at 9 pm identified ND from a household which uses the TV and radio during the night. This result indicated that the greater the time difference, the more ND the residents of a household experience. Ref. [29] investigated aircraft noise and found that night flights result in an average of nearly five times more discomfort than the flights during the day. This result is due to the insensitivity of residents to noise from 6 a.m. to 11 p.m. because they are busy and exposed to various noises within this period. The aforementioned studies imply that ND can occur and be significant due to the differences in the usage time of electrical appliances between neighboring households.

Although many studies on electricity consumption and noise discomfort were conducted separately, investigations on ND assessment based on electricity consumption patterns have not been attempted up to this day. In this study, a method that utilizes electricity consumption data to assess ND in households in a collective residential building based on the differences in the usage time of electrical appliances between neighboring households is proposed. The proposed method is explained in Section 3, and a case study of a campus apartment building is presented in Section 4 to demonstrate the application of the proposed method.

3. Method

The proposed method to assess noise discomfort caused by electrical appliances between neighbors includes four steps: data collection and preprocessing, residential units clustering, ND modeling, and ND evaluation (Figure 1). All steps described in this section are explained in detail through a case study.

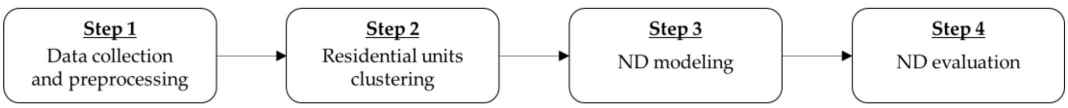


Figure 1. Research framework for noise discomfort (ND) assessment.

The first step in the proposed method is data collection and preprocessing for residential units clustering. In this step, data during certain periods are selected and then handled properly for clustering. First, the electricity consumption data of each unit during certain periods are extracted from a data repository. The extracted data include six features: time, sensor name, current, voltage, reactive power, and active power. Among the six features, time and active power are selected for clustering. Second, an integrated data set is made by combining separate active power data of each unit into one data set based on the time. The integrated data set is required to cluster units based on the time and amounts of electricity consumption. Finally, missing data are checked and the time interval of data for clustering is determined. Because different time intervals would lead to different clustering results, an appropriate interval reflecting the usage of residents' electrical appliances should be chosen. Through the preparation, the data formatted for clustering can be made.

The second step is to cluster residential units with similar electricity consumption patterns. Existing studies have used various time series clustering algorithms. The algorithms can be divided into five methods [30]: partitioning methods partitioning unlabeled data into K groups (e.g., K-means, K-medoids, Fuzzy C-means, and Fuzzy C-medoids), hierarchical methods aggregating data samples into a tree of clusters (e.g., an agglomerative algorithm and a divisive algorithm), model-based methods developing an unsupervised learning model and dividing groups (e.g., a self-organizing map), grid-based methods identifying a similar set of cells in a grid, and density-based methods separating subspaces where the objects have low density. In this study, the time series K-means clustering algorithm is used. The K-means clustering algorithm divides entire data into K groups based on their mean values [31]. This algorithm has been widely used due to its speed and ease of implementation [32,33]. The clustering of units is based on the amount and time of electricity consumption. This not only helps identify several typical groups but also enables us to find characteristic patterns of electricity consumption between groups [34–36]. These patterns are useful, since they provide accurate solutions to resolve the ND for each group. Through this step, several groups that consume electricity with similar patterns can be found as a result, and the clustering result should be validated.

The third step is to develop a model with some assumptions suitable for the assessment of ND between the units. The model applies the three features of each group found in the second step: peak time, start time, and end time. Peak time is defined as the time point when the electricity consumption is the highest. It is an important feature because it reflects the intensity of electrical appliance usage at the residential units [37,38]. Start time and end time signify the first increase time point and the last decrease time point of electricity consumption during the day, respectively. Both times are crucial features, representing the daily living activity of the unit [39,40]. The model examines the differences in time of the three features between units to assess the ND. The ND is the sum of the differences in peak time, start time, and end time between neighboring units. Because the model considers the ND caused by the units located left, right, below, and above, a unit normally receives the ND from the four directions, except for units located on the edge of building. A simple model considering the noise coming from the adjacent units located left, right, below, and above is introduced in Section 4, and variations in the ND assessment model are discussed in Section 5.

The final step is to calculate the ND using the model developed in the previous step. As the model assesses the ND between all units, it is possible to identify which households experience minimum or maximum ND level and the sum of ND levels that residents of all households living in the building experience.

4. Results through a Case Study of a Campus Apartment Building at POSTECH

In this section, we explain the method introduced in the previous section through a case study of a campus apartment building at POSTECH. POSTECH has developed an AMI and IT platform, called Open Innovation Big Data Center, to measure, collect, store, and share electricity consumption data on the campus. Various types of 288 smart meters were installed in seven campus buildings with different characteristics. The apartment building selected for this case study is one of these seven buildings. The selected 15-story apartment building comprises 75 units (five units on each floor). Each unit has the same structure, containing a bedroom, a bathroom, a kitchen and living room, and a balcony. The residents of this building are mainly married researchers and graduate students. As in any other residence, they use various electrical appliances, such as refrigerators, washing machines, and computers. The collected data include information on the time and amount of electricity consumption of each unit. Therefore, the usage time of electrical appliances can be extracted from these data. Usage times vary due to the different lifestyles of the household residents. For example, the usage times of kitchen appliances, such as microwave ovens and blenders, are different because residents have different dietary habits. These differences in the usage time of electrical appliances may cause ND between neighboring units. As the residents spend much time in the campus apartment building, it is important to understand and reduce the ND to provide a high quality of life of residents [41].

The case study presented in this work was conducted according to the following four steps: data collection and preprocessing, residential units clustering, ND modeling, and ND evaluation. Each step is described in the following subsections.

4.1. Data Collection and Preprocessing

The first step is data collection and preprocessing for residential units clustering. Electricity consumption data were collected from each unit at every second during the spring semester from 18 February to 7 June 2019 (the data collected were the power consumption levels in milliwatt (mW) units). This period was selected because many residents move in or out before or after the semester. Weekday data were only used because of the residents' schedule irregularity during weekends compared with that during weekdays [42,43].

A check on missing data was initially conducted. No missing data were found. Next, the units that did not reveal variations for the given period and used less than 30 W were considered to be empty units. 30 W is the minimum amount of electricity used by the residents in a household if they live there. Eight empty units were identified and excluded from the residential units clustering. Finally, units that exhibited a rapid electricity consumption amount reduction to a value of less than 30 W or a rapid increase to a value of more than 30 W and maintained their new electricity consumption amount for a certain period were identified. The identified units were deemed the units where residents moved out or in during the semester under investigation. Twelve units were identified and excluded from the residential units clustering due to insufficient data. Consequently, 55 units were confirmed as the units where the household residents lived without moving in or out during the semester under investigation.

The determination of the proper time interval is important for the extraction of meaningful information regarding the electrical appliance usage patterns. Aggregated data for 15-min, 30-min, and 1-h intervals, which are frequently used to determine patterns of electricity or electrical appliance usage, were compared in several studies [5,44,45]. The data comparison in the three intervals indicated that 1-h interval data sufficiently demonstrate the variations in electricity consumption. Accordingly, the 1-h interval was employed, and hourly data averaged over an hour were generated. Finally, the hourly 77 weekday data for each unit were transformed to hourly one-day data on average. Numerous studies have verified the similarity of electricity consumption patterns during weekdays [37,46], which confirms the rationale of this transformation. Other studies [47,48] also utilized the daily average electricity consumption data to cluster households and revealed the characteristics of each group. In summary, the one-day data of 55 units were utilized for the residential units clustering.

4.2. Residential Units Clustering

In this step, residential units with similar electricity consumption patterns are clustered. Since the households in the building include researchers and graduate students who might have similar daily working schedules, they may be clustered into several groups. A time series K-means clustering algorithm was utilized, and the initial number of clusters was set to three using the elbow method [49]. The three centers were randomly selected, and then each unit was assigned to the nearest cluster by the algorithm. After the assignment, the centroids of new clusters were computed. This process was repeated until a locally optimal partition was attained [50]. Silhouette analysis [51] was performed for clustering validation, and the results demonstrated that the silhouette values of all clusters were over 0.60, indicating a reasonable splitting of clusters [52,53].

The result of clustering is presented in Figure 2. The household residents living in the units and included in group 1 (orange lines) use a typical electricity consumption ranging from 100 W to 350 W. The electricity consumption increases in the morning (from 05:00 a.m.), decreases after 12:00 p.m., and then increases again, maintaining a high consumption after 04:00 p.m. The household residents living in the units and included in group 2 (blue lines) show a pattern similar to that of group 1. Although the household residents in group 2 have similar consumption times to those in group 1, they generally consume a minimum amount of electricity ranging from 40 W to 250 W. The household residents living in the units and included in group 3 (green lines) consume a considerable amount of electricity ranging from 100 W to 550 W. The electricity consumption gradually increases from 05:00 a.m. to 11:00 a.m. and stabilizes afterward. It then decreases after 19:00 p.m., which is quite early compared to other units in different groups. The number of units in each group was 27 (49%), 19 (35%), and 9 (16%), respectively.

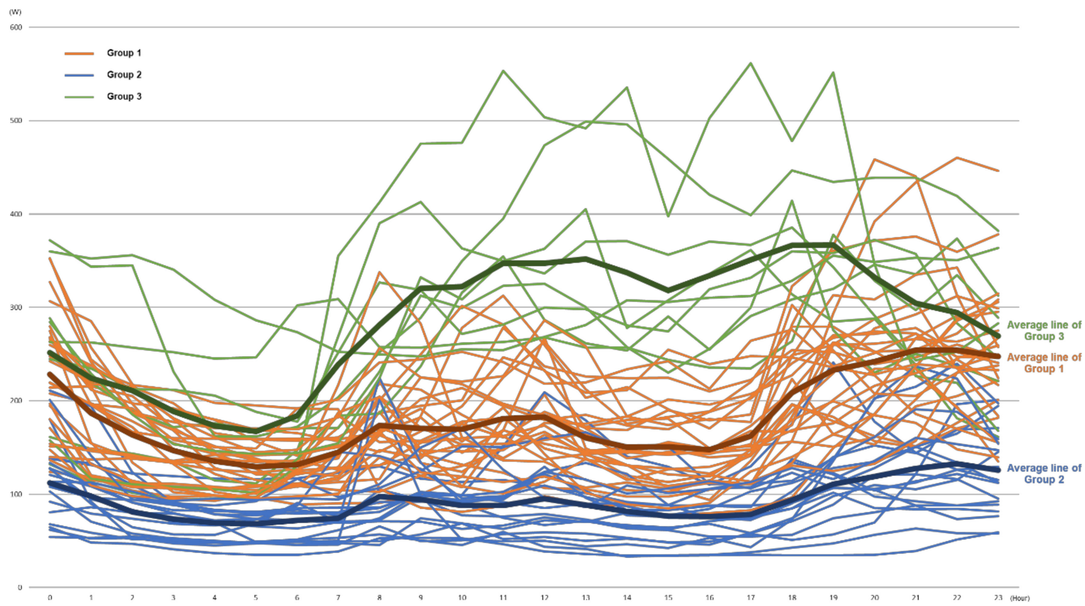


Figure 2. Clustering result for 55 units based on electricity consumption.

The three thick lines shown in Figure 2 represent average amounts of electricity consumption for each group. The three average lines were considered as representatives of each household in the corresponding groups. Three features, namely, peak time, start time, and end time, were extracted based on these lines. Peak time is the time when the amount of electricity consumption is the highest during the day. Peak time is an important feature, which reflects the time and amount of electricity consumption by electrical appliances at residential units [37,38]. Start time and end time are the first increase time and the last decrease time of electricity consumption during the day, respectively. Both times are crucial features, which represent the daily living activity of the unit [39,40]. The peak time, start time, and end time of each group are presented in Table 1. The end time and peak time of each group are the same, and the start time of the three groups is at 05:00 a.m.

Table 1. Peak time, start time, and end time of each group.

Group \ Feature	Peak Time	Start Time	End Time
Group 1	21:00	5:00	21:00
Group 2	22:00	5:00	22:00
Group 3	18:00	5:00	19:00

4.3. ND Modeling

In this step, a model suitable for the assessment of ND between the units is developed. This model applies the three features of each group obtained in the previous section: peak time, start time, and end time. The three features represent the residents' pattern of electricity consumption. The difference in patterns of electricity consumption between neighboring units causes the ND. In this respect, the model examines the differences in time of the three features between units to assess the ND. The amount of electricity consumption can also be considered for the ND assessment, which will be discussed in Section 6. The following three assumptions are adopted to simplify the model. These assumptions can be relaxed as appropriate. Some examples of assumption relaxation are discussed in Section 5.

Assumption 1. *ND is caused by the noise that only comes from neighboring units located left, right, below, and above, and not from other distance units.*

Assumption 2. *The ND level does not change in the four directions: left, right, below, and above.*

Assumption 3. *The ND level increases linearly with the differences in the time of the three features between units.*

An example of the ND experienced by the household residents living in unit 202 that was caused by the neighboring households is presented in Figure 3. The ND (ND) is the sum of sub-NDs (SND_d). The subscript d denotes the direction of units causing ND and represents the four directions: adjacent left (SND_{left}), right (SND_{right}), below (SND_{below}), and above (SND_{above}) units. In Figure 3, SND_{left}, SND_{right}, SND_{below}, and SND_{above} represent the ND caused by neighbors living in units 201, 203, 102, and 302, respectively. Each sub-ND is the sum of the time differences ($TD_{d,t}$) between the adjacent neighbors. The subscript d is similar to the one used for the directions of the ND, and the subscript t denotes the three features; peak time, start time, and end time. For example, $TD_{left,peak}$, $TD_{left,start}$, and $TD_{left,end}$ denote the difference in the peak time, start time, and end time caused by the adjacent left unit, respectively.

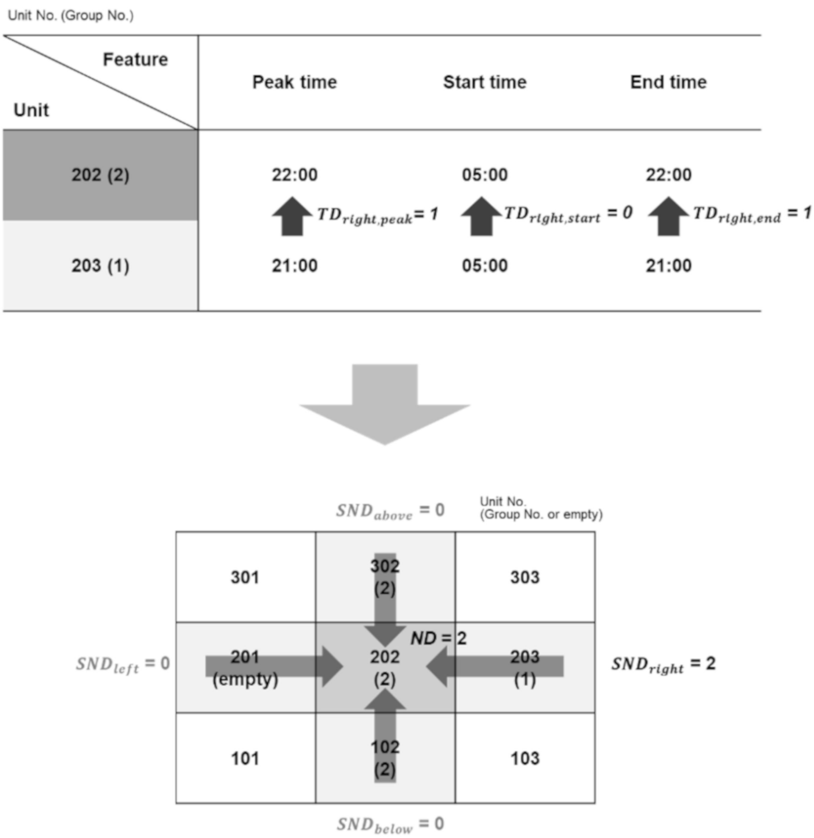


Figure 3. ND experienced by the household residents living in unit 202.

Figure 3 denotes that the household residents living in unit 202 do not experience ND caused by unit 201, which is one of the empty units. In the ND assessment, empty units do not cause and experience ND. ND does not originate from units 102 and 302 either, because the household residents living in these units are included in the same group in unit 202. However, the ND is caused by the household residents living in unit 203. This household is included in a different group. Thus, the household has a different peak time, start time, and end time. Based on Table 1, there is a one-hour gap between the peak times and end times of groups 2 and 1. Therefore, the ND level, which the household residents living in unit 202 experience, is 2. ND can similarly occur in other households.

The ND based on the proposed model can be calculated as follows:

$$ND = SND_{left} + SND_{right} + SND_{below} + SND_{above}, \tag{1}$$

$$\begin{aligned} SND_{left} &= TD_{left,peak} + TD_{left,start} + TD_{left,end}, \\ SND_{right} &= TD_{right,peak} + TD_{right,start} + TD_{right,end}, \\ SND_{below} &= TD_{below,peak} + TD_{below,start} + TD_{below,end}, \\ SND_{above} &= TD_{above,peak} + TD_{above,start} + TD_{above,end}, \end{aligned} \tag{2}$$

where SND_{left}, SND_{right}, SND_{below}, and SND_{above} are the sub-NDs caused by the noise coming from the adjacent units located left, right, below, and above, respectively. Each of the four sub-NDs is the sum of the differences in peak time, start time, and end time between neighboring households. *ND* denotes the ND the household residents experience from four neighboring households. Therefore, the *ND* for each of the 55 units can be evaluated.

4.4. ND Evaluation

The ND of each unit can be calculated using Equations (1) and (2). The sum of ND levels, which residents of all households living in the apartment building experience, is 304 per day. Considering the empty units that do not cause and experience ND and units located at the edge of each floor, the potential maximum and minimum sum of ND levels of all households is 9798 and 0 per day, respectively. The maximum value is estimated from the situation when a gap of usage time of electrical appliances between all neighboring households is the most different (e.g., a household uses appliances at 00:00 a.m. but the next household uses appliances at 23:00 p.m.). Based on the range, the evaluated sum of ND levels, 304 per day, is not huge. The average ND level, which is experienced by the residents of 55 households from adjacent units, is 5.53 per day. ND originates from the differences in the peak times and end times occurring during the night from 19:00 to 22:00 p.m. due to the absence of differences in the start times among groups (Table 1).

The heat map presented in Figure 4a indicates the ND levels of each unit. The largest ND level is 16 per day, and the household residents living in units 402, 602, 1102, and 1502 experience this ND. On the other hand, seven units do not experience ND from neighboring households.

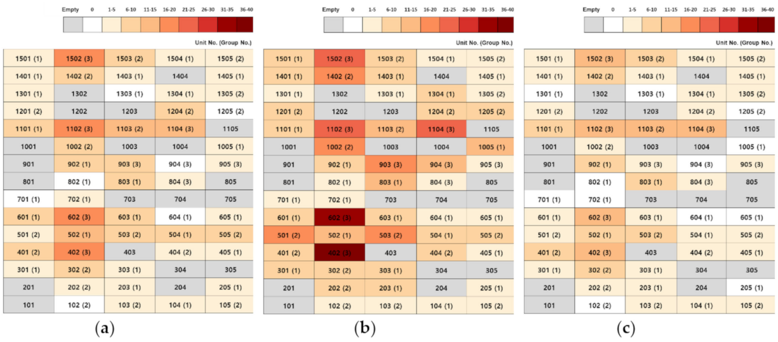


Figure 4. Heat maps of the ND levels of each unit (**a**) with original assumptions; (**b**) with relaxed Assumption 1; (**c**) with relaxed Assumption 2.

5. Discussion

The model introduced in Section 3 can be modified to suit the given circumstances. The variations in the ND assessment model and measures for ND alleviation are discussed in this section. In Section 3, three assumptions were adopted to simplify the model, but the model assumptions can be relaxed considering various real situations. In this section, we present variations in the ND assessment model with model assumption relaxation. Subsequently, several measures for ND alleviation of units are suggested considering the characteristics of a campus apartment building.

5.1. Variations in the ND Assessment Model

The three assumptions introduced in Section 3 need to be relaxed, depending on the given circumstances. For example, according to Assumption 1, the residents of a household experience ND only from the adjacent units located left, right, below, and above, and not from other distant units. However, in certain circumstances, ND may be attributed to units located further away or diagonally. An example of relaxing Assumption 1 considering the units located diagonally is depicted in Figure 5. A modified model for the evaluation of ND of each unit according to the relaxed Assumption 1 can be developed by adding variables representing diagonal directions to the original model. The ND of each unit considering the relaxed Assumption 1 (*ND_A1*) can be evaluated as follows:

$$\begin{aligned} ND\_A1 &= SND_{left} + NSD_{right} + SND_{below} + SND_{above} \\ &+ SND_{leftdown} + SND_{leftup} + SND_{rightdown} + SND_{rightup}, \end{aligned} \tag{3}$$

$$\begin{aligned} SND_{leftdown} &= TD_{leftdown,peak} + TD_{leftdown,start} + TD_{leftdown,end}, \\ SND_{leftup} &= TD_{leftup,peak} + TD_{leftup,start} + TD_{leftup,end}, \\ SND_{rightdown} &= TD_{rightdown,peak} + TD_{rightdown,start} + TD_{rightdown,end}, \\ SND_{rightup} &= TD_{rightup,peak} + TD_{rightup,start} + TD_{rightup,end}, \end{aligned} \tag{4}$$

where *ND_A1* is the ND caused by the eight directions. $SND_{leftdown}$, SND_{leftup}, $SND_{rightdown}$, and $SND_{rightup}$ in Equation (3) are added to represent the sub-NDs caused by the units located diagonally left down, left up, right down, and right up, respectively. Each of the added four sub-NDs is the sum of the differences in peak time, start time, and end time between neighboring households. This sum is similar to the sum described in Equation (2). Other variables have similar meanings to those presented in Equations (1) and (2).

Based on the relaxed model described in Equations (3) and (4), the sum of ND levels which all household residents living in the apartment building experience is 528 per day. This is larger by 224 (a 73.68% increase) than that calculated based on the original model. The maximum and minimum sum of ND levels of all households is 20,838 and 8 per day, respectively. Considering the changed range, the original model, the evaluated sum of ND levels, 528 per day, is not huge. Each household experiences an average ND level of 9.6 per day from adjacent units.

The heat map illustrated in Figure 4b indicates the ND levels of each unit considering the relaxation of Assumption 1. A comparison of Figure 4a,b reveals an increase in the ND levels and the number of units experiencing ND. The largest and smallest ND levels are 36 and 2, respectively. Furthermore, units which do not experience ND from their nearest units are non-existent. This result demonstrates that ND is intensified when Assumption 1 is relaxed.

Similarly, Assumption 2 can also be relaxed. This assumption indicates that the ND level does not change in the four directions: left, right, below, and above. However, in practice, the ND level may vary. Households can be easily exposed to noise from next door rather than from below or above [54]. Thus, a relaxed model which assigns different weights based on the directions is suggested. For example, the equation for the ND evaluation of households when Assumption 2 is relaxed (*ND_A2*) can be written as follows:

$$ND\_A2 = 1.2\ SND_{left} + 1.2\ SND_{right} + 0.8\ SND_{below} + 0.8\ SND_{above}, \tag{5}$$

where all variables have similar meanings to those in Equations (1) and (2). Each weight (1.2, 1.2, 0.8, and 0.8) represents the impact of left, right, below, and above units, respectively, based on the previous study [54]. The sum of weights is similar to that of the original model. These weights can be changed according to the building environment and structure.

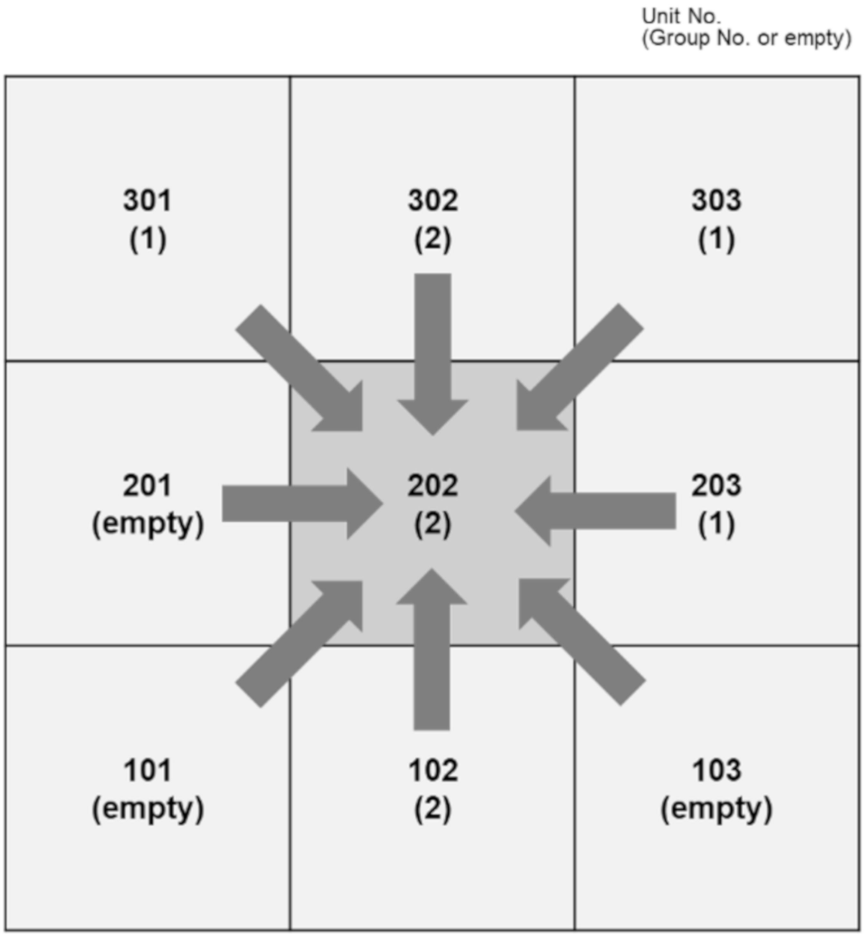


Figure 5. Example of relaxing Assumption 1.

The ND of each unit was calculated according to Equation (5). The sum of ND levels which all household residents living in the apartment building experience and the average ND level of each household are reduced from 304 to 246.4 per day and from 5.53 to 4.48 per day (a 18.95% decrease). The maximum and minimum sum of ND levels of all households is 9715.2 and 0 per day, respectively. Considering the changed range, the evaluated sum of ND levels, 246.4 per day, is not huge. As the changed range is not much different from the range based on the original model, the sum of ND levels with the relaxed Assumption 2 is considerably reduced. Similarly, the largest ND level is reduced from 16 to 14.4 per day (a 10% decrease).

The heat map illustrated in Figure 4c indicates the ND levels of each unit when Assumption 2 is relaxed. Compared with Figure 4a, the ND levels of each unit and the number of units experiencing ND decrease, as shown in Figure 4c. For example, the largest ND level is 12, and 12 units do not experience ND at all. This result implies that the results of the ND assessment can be changed depending on the weights assigned to the directions. Thus, the weights must be carefully determined considering various contexts and building environments.

Given below are two examples of relaxing the initial assumptions. The first example presents the case when the ND caused by other distant units, in addition to the adjacent units located left, right, below, and above is considered, while the second example presents the case when the weights for sub-NDs caused by adjacent units can be differently assigned depending on the direction of the units. These examples show that the model can be modified to reasonably assess the ND caused by units placed at various locations of the apartment building (i.e., the ND propagated from distant units). In addition, the relaxation of these assumptions may vary considering numerous aspects such as time types, household characteristics, and weather. For example, ND does not increase linearly with the difference in time of the three features between units, as Assumption 3 suggests. ND may increase exponentially when it occurs late at night, when household residents are sleeping [29]. Thus, changing the ND level based on the noise occurrence time is necessary. Considering the examples introduced, various situations should be considered to develop realistic ND assessment models.

5.2. Measures for ND Alleviation

The campus apartment building used for the ND investigation has some unique characteristics. One is that household residents are relatively free to move in or out. The university manages the movements, which frequently occur during the beginning and end of a semester and vacation. This characteristic provides the university with the possibility of alleviating ND by properly assigning households to the units.

The re-calculation of the sum of ND levels which all household residents living in the apartment building experience is possible in case the assignment of households to the units is changed. The aim of this section is to show how much the ND level can be reduced by properly assigning households to the units. The mathematical formulation of an extreme case where all households of the 55 units are assigned to 75 units from scratch to minimize the sum of ND levels is given below.

Minimize

$$\sum_{i=1}^{I}\sum_{j=1}^{J-1}\sum_{k=1}^{K}\sum_{k'=1}^{K} D_{kk'} \cdot y_{ijkk'} + \sum_{i=1}^{I}\sum_{j=2}^{J}\sum_{k=1}^{K}\sum_{k'=1}^{K} D_{kk'} \cdot z_{ijkk'} + \sum_{i=1}^{I-1}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{k'=1}^{K} D_{kk'} \cdot w_{ijkk'} + \sum_{i=2}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{k'=1}^{K} D_{kk'} \cdot u_{ijkk'} \quad (6)$$

subject to

$$\sum_{i=1}^{I}\sum_{j=1}^{J} x_{ijk} = 1,\ \forall k \in K$$

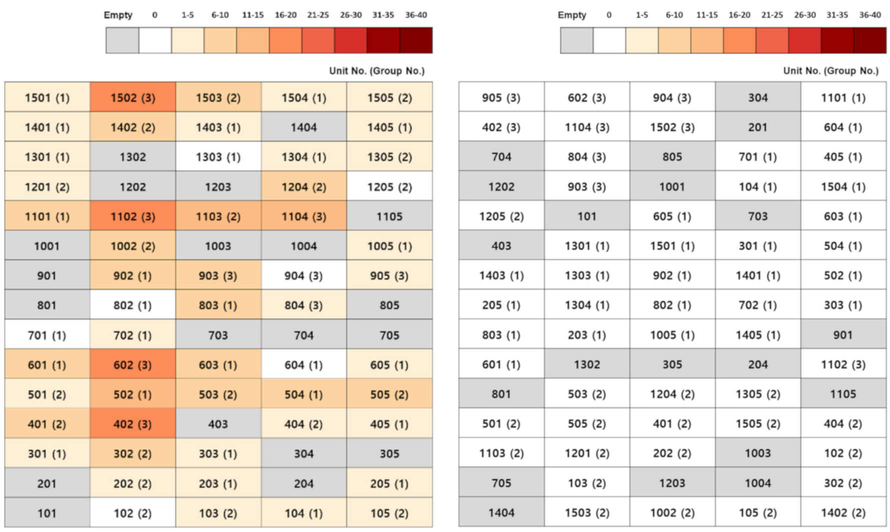
$$\sum_{k=1}^{K} x_{ijk} = 1,\ \forall (i,j)\ pairs$$

$$x_{ijk} \in \{0, 1\}, \forall i \in I,\ j \in J,\ k \in K$$

$$y_{ijkk'}, z_{ijkk'}, w_{ijkk'}, u_{ijkk'} \in \{0, 1\},\ \forall i \in I,\ j \in J,\ k, k' \in K, k \neq k'$$

where subscripts *i*, *j*, and *k* denote the unit floor, unit number, and household's group, respectively. $D_{kk'}$ represents the ND which the household included in group *k* experiences from the household included group in k'. $D_{kk'}$ is the sum of the differences in peak time ($d_{kk',\ peak}$), start time ($d_{kk',start}$), and end time ($d_{kk',end}$) between neighboring households. The above equations for $D_{kk'}$ are similar to Equations (2) and (4). $y_{ijkk'}$, $z_{ijkk'}$, $w_{ijkk'}$, and $u_{ijkk'}$ indicate whether the household included in group k' lives adjacently left, right, below, and above the household included in group *k* that lives in the *ij* unit, respectively. Therefore, the four variables are binary, receiving the values 0 or 1. The assignment of only one household to one unit is guaranteed by the addition of constraints. The minimum entire ND level of the apartment building can be found by identifying the optimum assignment of all households.

The new assignment of households that minimizes the sum of ND levels which all household residents living in the apartment building experience is determined by the proposed model. The difference between the result obtained using the original model and the optimization result is shown in Figure 6a,b. The new assignment reduces the sum of ND levels to 0, that is, completely removes the ND of the household in Figure 6b. Households included in the same group are closely located, and empty units are properly assigned to minimize the ND level. The switching of units between households included in the same group produces the same result.



(**a**) (**b**)

Figure 6. Comparison of heat maps representing the ND levels of each unit between (**a**) the result obtained using the original model and (**b**) the optimization result.

The practical implementation of the introduced scenario is difficult because the assignment is costly, and some households may prefer not to move to different units. Considering such constraints, several realistic measures can be proposed. For example, a model for the reduction of the largest ND level can be established. The largest ND level is 16 per day in the original model, and four units experience this ND. If residents in these four households continuously express complaints, the university may consider reassigning several households but not all households. In this case, some models capable of determining the necessary measures of the assignment can be developed. It is possible to decide the number of households that should be assigned. The units to where the households should move to reduce the largest ND level below a certain level can be determined. In addition, identifying the units to where the households should move to achieve maximum ND level reduction when the number of households able to move is limited could also be possible. In a real-life situation, it would be virtually impossible to ask tenants to change their units. Nonetheless, the information on the ND of neighbors can be provided to each unit and residents might utilize this information to alleviate the ND by adjusting their electricity usage time between neighboring units. Finally, the ND information should be regularly updated to reflect changed patterns of electricity consumption over time.

6. Conclusions

In this study, a method that applies electricity consumption data for the assessment of ND was proposed. The proposed method was demonstrated through a case study of a campus apartment building. Initially, the electricity consumption data were collected and preprocessed. Subsequently, based on the amount and time of electricity consumption, the units were clustered. Next, an ND assessment model was developed, and the ND was evaluated based on this model. The modification of the ND assessment model by relaxing the initial assumptions using two examples was also discussed. Additionally, measures for ND alleviation were described with an example identifying the optimum assignment of households to reduce the entire ND level.

The proposed method is the first attempt that utilizes electricity consumption data to assess the ND between neighboring households. The electrical appliance usage patterns, which were extracted from the electricity consumption data, are employed to assess the ND. It is very difficult for the residents to remember when and how much ND they experienced after some time. However, the collected electricity consumption data allow one to identify the time-point and assess the resulting ND level. The main limitation of this study is the lack of an empirical validation of the model. The accuracy of the ND assessed by the proposed model has not been tested empirically. For validation, a follow-up study with a questionnaire survey for residents can be conducted. It would be appropriate to compare the ND which the residents evaluate themselves with the ND evaluated by the model in an experimental setup. If no significant difference is observed between the two results, the model can be adopted to assess the ND.

Several future research issues are suggested. First, advanced data aggregation and clustering methods can improve the ND assessment results. The case study presented in Section 3 utilized the hourly one-day data on the average refined from weekday data. Various time intervals from 1-min to 1-month, and the seasonality of electricity consumption can be considered to find the residents' electricity consumption patterns. Diverse representative values, such as median and mode, can also be used when aggregating the raw data. Additionally, different clustering methods, such as the Agglomerative Hierarchical clustering [55] and Fuzzy clustering [56], can be employed. Agglomerative Hierarchical clustering is a robust algorithm in the presence of noise, and Fuzzy clustering provides a degree of membership to each datum, which helps improve the performance of clustering analysis and interpret the results [57]. Second, the collection and use of quantitative data that are directly related to ND, such as the amount of electricity consumption, noise decibel, or questionnaire responses on residents' perceptions, would make the ND assessment more convincing. For example, even when two households have the same peak time, start time, and end time of electricity consumption, the amounts of electricity consumption of the two households at these time points may be different. This would imply that they use different appliances, which cause different noise levels. Therefore, considering the amount of electricity consumption in addition to the differences in electricity consumption times can help estimate the ND more accurately. Third, the identification of the electrical appliances used through electricity consumption data can support the ND assessment. The non-intrusive appliance load-monitoring methods [58] have recently been introduced. If the appliances used can be identified, the ND caused by the appliances can be estimated. For example, ND would be substantially larger when a neighboring household uses a vacuum cleaner instead of a computer. If the noise decibel data of the identified appliances are provided, ND can be assessed more accurately. Finally, the proposed method can be combined with a reward model to encourage households to reduce the ND they cause their neighboring households. Rewards such as the reduction of electricity charges or the donation of coupons to campus stores can help residents change their electricity consumption patterns. This, in turn, can reduce ND. Updated models can provide a balance between the ND level, which needs to be reduced, and the rewards provided to households. The integration of rewards will provide a powerful motivation to actively engage households in noise alleviation activities.

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