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Energy Consumption Model Based on User Behavior to Support Solar Panel Selection: Case Study of Dental Clinic

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Abstract. *Electricity consumption continues to rise alongside population growth and infrastructure development. Unfortunately, the majority of energy consumption is still reliant on fossil fuels. Commercial buildings and residences are major contributors to electricity consumption, accounting for 63.04% of the total usage. In the healthcare sector, clinics and hospitals also require significant electrical energy, contributing to a 21% rise in national electricity demand. Additionally, occupants' behavior influences electricity consumption by 30%. Faced with these challenges, the use of renewable energy, such as solar power, holds great potential for providing sustainable energy. This research aims to simulate energy consumption to aid in the selection of solar panel technology, considering occupant behavior. By understanding accurate electricity consumption, solar panels that meet the needs can be chosen to ensure long-term sustainability. Simulation of electricity consumption using dynamic system methods is performed to acquire daily electricity consumption data, a critical criterion in solar panel selection. The study's results indicate that user behavior in utilizing electrical appliances significantly impacts overall energy consumption. The study implies the importance of understanding behavior to properly recognize actual electricity consumption.*

Keywords: *Energy consumption, simulation, system dynamic, user behaviour.*

1. Introduction

1.1. Motivation and background

Commercial and residential buildings are among the main contributors to electricity consumption, accounting for 63.04% of the total users (PLN Statistics, 2020). In the healthcare sector, clinics and hospitals also require substantial electrical energy for medical equipment, lighting systems, heating, and cooling. Healthcare facilities experience a 21% rise in energy consumption. (Bawaneh et al., 2019). The consistent energy demand and high electricity requirements in medical environments underscore the importance of efficient energy management and usage.

Dental clinics, as part of the healthcare sector, also have significant electricity consumption. Daily operational activities, such as using medical equipment, lighting, and heating/cooling systems, require a stable energy supply. Dental clinics consume the most electricity among primary healthcare facilities due to their consistent use of medical procedures with complete equipment in patient care. Energy efficiency and the choice of renewable energy sources are critical considerations in managing dental clinic energy consumption.

Based on the Indonesia Energy Outlook 2022, the government plans to accelerate the adoption of renewable energy. This is underscored by the significant potential of solar energy, particularly in rural areas of Indonesia. High energy consumption also impacts dental clinic operational costs. High electricity costs can affect profitability and the sustainability of clinic operations. Therefore, energy efficiency and the use of renewable energy sources can help reduce service costs and enhance dental clinic sustainability.

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User behavior, whether in commercial buildings or residences, significantly influences energy consumption. Habits related to electrical appliance usage, room temperature settings, light usage patterns, and effective energy management can influence energy usage levels. User behavior affects 30% of electricity consumption (Chen et al., 2021). Furthermore, about 10% - 40% (Kim & Srebric, 2017) of energy usage can be reduced through occupancy-related factors in building operations. Particularly in clinics, the behavior of dental clinic users has a significant impact on electricity consumption. Efficient equipment usage, temperature control, and energy-consciousness can help reduce unnecessary electricity consumption. Education and awareness of efficient energy use can contribute to reducing environmental impact and operational costs.

Faced with current energy and environmental challenges, the use of renewable energy offers attractive opportunities. Renewable technologies, such as solar energy, hold significant potential for providing clean energy, reducing greenhouse gas emissions, and enhancing sustainability. Implementing renewable energy can decrease reliance on non-renewable energy sources and offer environmentally friendly solutions.

Solar energy, through the use of solar panels, is a promising option among renewable energy sources. The sun is an abundant and widely available renewable energy source in Indonesia (Indonesia Energy Outlook, 2022). Utilizing solar panels can generate clean and sustainable electricity, reduce greenhouse gas emissions, and cut long-term operational costs for dental clinics. The implementation of renewable energy, especially the use of solar panels, in dental clinics is vital for achieving sustainability and reducing environmental impact. Solar panels can generate electricity independently and provide a stable energy supply. Adopting solar panels in dental clinics can reduce dependence on non-renewable energy, save long-term operational costs, and provide significant environmental benefits.

Selecting solar panels as a renewable energy source for dental clinics comes with a number of facts and advantages. Indonesia receives abundant sunlight throughout the year, making it an ideal location for utilizing solar energy. Solar panels can be installed on the dental clinic's roof to generate electricity for operational activities. Other advantages include their long lifespan, ease of maintenance, and the enhancement of the dental clinic's image as an environmentally-conscious institution (Ismail et al., 2013).

In the face of electricity consumption challenges, the influence of user behavior, and the importance of sustainability, the adoption of renewable energy, especially the use of solar panels, is a prudent and fitting choice for dental clinics. In managing energy consumption, reducing emissions, and considering operational costs, the use of renewable energy sources can bring long-term benefits and drive sustainability in the healthcare sector.

Several previous studies have conducted research on solar panel selection for buildings. Research conducted by El-bayeh et al. (2021), Tamosiunas (2023), Seker & Kahraman (2021), Sasikumar & Ayyapan (2019), Wu et al. (2018), and Kozlov & Salabun (2021) highlight the importance of good selection criteria in obtaining appropriate solar panels.

Previous studies have shown that various factors can influence the selection of appropriate solar panels. However, one factor that has been incomplete in some previous studies is the importance of considering energy needs. Energy needs are a key success factor in solar panel selection (Shabbir et al., 2020). Not only understanding but also carefully considering energy needs is a primary factor in selecting sustainable solar panels (El-bayeh et al., 2021).

Based on previous research studies and the current context, it is evident that selecting the right renewable technology requires understanding actual needs. One approach is to simulate energy needs based on user behavior, which is the primary variable (Piselli & Pisello, 2019). User behavior within buildings is a critical factor influencing energy consumption (Sun & Hon, 2016).

Previous research on solar panel selection has attempted to use various methods based on specific criteria. Various methods and criteria are combined to obtain a selection model capable of providing the most suitable solar panel choices. Previous research studies indicate a lack of consideration for sufficient energy consumption in solar panel selection. However, satisfying electricity needs is the primary objective of choosing solar panels as an energy source (El-bayeh et al., 2021).

Energy consumption itself depends on user behavior, requiring attention to electricity needs. Previous research studies have investigated electricity consumption considering user behavior. Various methods and types of behavior have been combined to create energy consumption models that can represent actual conditions. The scarcity of studies on the selection of renewable technologies considering energy needs highlights a gap in previous research. This study aims to address this gap by exploring energy consumption and user behavior, particularly in relation to energy consumption. It supports the selection of appropriate renewable technologies based on energy needs. Choosing renewable technologies that can effectively meet energy demands contributes to their sustainable use.

1.2. Organization of the paper

This article is organized as follows: the first section discusses the rationale for conducting the research, literature review, and the contribution of the conducted study. The second section covers the research methodology, including the subject and stages. The third section explains the process of the conducted selection in the study. The fourth section presents the results of the selection process in the form of outcomes and discussions. Finally, the fifth section contains the conclusion and managerial implications of the study's findings.

2. Literature Review

Several previous studies have explored energy consumption simulation based on user behavior. De bakker et al. (2017) investigated the influence of various occupancy patterns in office spaces on energy savings relative to control strategies with different control zone sizes. They employed stochastic modeling to estimate occupancy patterns, as this method can account for uncertainties. To validate the model, simulation results were compared with previous studies and actual measurements, demonstrating that the simulation can provide realistic occupancy patterns. Furthermore, the application to a case study of offices with variations in user distribution (occupations) and office policies was further analyzed to determine the potential energy savings associated with occupancy pattern variations. The relative energy savings potential from different control strategies showed minimal differences for each test case. Additionally, the results indicated that individual occupancy pattern variations only slightly affected energy savings.

Sun & Hon (2016) asserted that user behavior in buildings is a key factor influencing energy usage in buildings. Energy-efficient behavioral solutions exhibit significant electrical savings potential. It is important to estimate to what extent user behavior can save energy to forecast more effective behavior changes, thereby supporting more effective energy policies. This study introduced a simulation approach to estimate the energy savings potential from user behavior. The primary finding of this research is that based on simulation results, various user behavior types can achieve significant energy savings, reaching up to 22.9% for individual measures and up to 41.0% for integrated measures. The main energy savings were obtained from user behavior that originated from avoiding energy wastage in unoccupied rooms, particularly for lighting, plug loads, and HVAC systems. Occupancy schedules significantly influenced energy savings from user behavior.

Piselli & Pisello (2019) evaluated different static and stochastic occupancy models' abilities to predict actual user behavior in office buildings and building energy performance. To achieve this goal, environmental and energy parameters related to user behavior were extensively monitored in five equivalent office rooms in central Italy to develop a data-based occupancy model. Thus, three existing standard static and stochastic occupancy models and five developed data-based models were analyzed in terms of (i) short-term simulated parameter trends, i.e., daily, compared to actual monitoring data and (ii) the building's total energy consumption over the long term, i.e., annually. The results indicated that the existing standard occupancy models did not represent specific user attitudes and peak energy demand or average seasonal behavior, both in the short and long terms.

Mahdavi et al. (2016) designed a prediction method for plug loads in offices. This study compared a simple method with a more detailed probabilistic method to assess both methods' capabilities. Model evaluation results showed that the non-stochastic model provided reasonable predictions of annual energy usage related to plug loads. However, the stochastic plug load model, along with the stochastic occupancy model, excelled in predicting peak and time-dependent (interval) load distributions. Furthermore, the study's results demonstrated an interesting relationship between user presence, installed equipment power, and resulting electricity usage. Comparing model predictions with observed data indicated that the simple method could represent energy consumption patterns with a more complex probabilistic approach.

Uddin et al. (2022) discussed user behavior as a critical parameter for evaluating building energy consumption. Additionally, user behavior can substantially influence the choice of technology to improve building energy efficiency. This study investigated the impact of energy conservation-related user behavior in the context of interior layout configurations using a holistic approach that employed Agent-Based Modeling (ABM), Systems Dynamics (SD), and Building Information Modeling (BIM). The research successfully developed and applied a hybrid modeling approach to promote energy-efficient systems for buildings and identified key players involved in energy savings through appropriate user interventions. This study also offered a validation approach using real sensor data collection systems adapted to enhance the reliability, confidence, and robustness of the proposed model. The validation and suitability of the proposed model are crucial to make it a representative model used during the simulation process.

Hon & Sun (2017) introduced a simulation framework to quantify the impact of user behavior on energy savings from Energy Conservation Measures (ECMs). Three user behavior styles—conserving, normal, and wasteful—were defined to represent different energy awareness levels in controlling HVAC, windows, lights, and plug loads. These behavior styles do not always represent realistic user behavior in buildings but rather delineate the boundaries between energy savers and energy wasters. This framework was then applied in a pilot study to evaluate the differences in ECM energy savings among different behavior styles. The main finding of the study is that user behavior styles significantly influence building energy usage.

Buildings occupied by energy wasters can consume over twice the energy consumed by energy savers. Additionally, for ECMs not dependent on user behavior, which are entirely technology-driven and have little user interaction, such as reducing light power, equipment power, building property improvement, and HVAC system and natural lighting control efficiency enhancement, the percentage of energy savings is minimally influenced by user behavior styles. For ECMs dependent on user behavior, which have strong user interaction, such as natural cooling and ventilation systems, the percentage of energy savings is significantly influenced by user behavior styles.

Various studies on energy consumption simulation based on user behavior have been conducted using different methods. However, research that considers user types in the simulation process is still scarce. This study aims to simulate energy consumption based on user behavior while considering user types to support the solar panel selection process. This research contributes to developing a simulation that provides results closer to actual needs by considering user types. The results are expected to offer more accurate guidance in deciding the best solar panels to meet clinic requirements.

3. Methodology

3.1. Method

The calculation of electricity consumption is further discussed because, based on El-bayeh et al. (2021), this criterion is a primary factor in selecting solar panels. Electricity consumption calculation is performed using a dynamic system to obtain daily electricity consumption values based on user behavior. User behavior is essential to consider as it influences electricity consumption by 30% (Chen et al., 2021). Additionally, around 10% - 40% of energy can be reduced through factoring in human aspects in building usage operations (Kim & Srebric, 2017).

The calculation of daily electricity consumption is aimed at obtaining more accurate electricity requirements or representing actual needs. The current capabilities of solar panels are limited in meeting electricity needs due to stability of power supply and efficiency in converting solar radiation into electricity. However, with technological advancements, solar efficiency continues to improve to the point where it can independently meet daily electricity consumption. Moreover, combinations of various renewable energy technologies also enable self-sufficiency in meeting electricity needs.

The use of a dynamic system in the calculation is chosen due to its ability to illustrate variable user behavior in electricity consumption. According to Uddin et al. (2022), electricity consumption in buildings varies greatly and is influenced by numerous factors. Dynamic systems help identify non-linear usage behavior. Uddin et al (2022) employed a dynamic system approach to estimate room electricity consumption based on usage behavior while considering interior room layouts. Research findings revealed a strong connection between user behavior, room layout, and electricity consumption. Given this application, the dynamic system was chosen due to its versatility in both broad and specific contexts, offering system dynamics. The dynamic system simulation in this study is conducted using Powersim software.

Electricity consumption calculation is performed on a dental clinic as a case study. The dental clinic was selected due to its spaces having dynamic user activities related to electrical appliances. Dental clinics engage in more medical procedures with the highest electricity consumption compared to other primary care clinics. The calculation of electricity consumption in this case study is expected to be applicable to similar calculations in various room types and healthcare facility buildings.

3.2. Model

The energy consumption model is a model that calculates the electricity usage by users based on the utilization of electrical appliances within a specific time period. Modeling the electricity consumption scenario is constructed by presenting a feedback structure that represents cause and effect. Scenarios in this modeling employ a business-as-usual scenario, situating the model under normal conditions when electricity consumption is used as intended.

In this modeling, the electricity consumption of the clinic is influenced by the following activities:

1. Variation in the number of clinic patients requiring medical procedures each day.

2. Overall use of electrical appliances by each user following their electricity consumption behavior.

In the calculation of electrical energy consumption, the ultimate output is the total amount of electricity consumed by the clinic based on the influence of the electricity consumption behavior of each user. A user is an individual who uses electrical appliances, while user behavior refers to the user's habits regarding the amount and timing of electrical appliance usage.

Electricity users in the clinic are categorized into five types of usage behavior:

1. Behavior of building electrical appliance usage.
2. Behavior of doctor's electrical equipment usage.
3. Behavior of medical procedure electrical usage.
4. Behavior of nurse's electrical equipment usage.
5. Behavior of administrative electrical equipment usage.

Behavior regarding electricity consumption consists of five types of usage:

1. Lighting usage
   Usage of electrical appliances in the form of lighting, both indoor and outdoor.
2. Thermal comfort usage
   Usage of electrical appliances to maintain a comfortable temperature.
3. Plug load usage
   Usage of electrical appliances plugged into outlets or power sources.
4. HVAC control usage
   Usage of cooling and heating systems to maintain desired room conditions.
5. Window control usage
   Usage of windows to maintain proper air circulation and temperature.

In this study, the calculation of electricity consumption focuses on three usage behaviors: lighting, plug load, and HVAC control.

The conceptualization of the system is represented in the form of a causal loop diagram, which includes identifying crucial factors or highly influential variables believed to play a role within a system. The feedback structure forms the foundational blocks of

These five user behavior categories indicate the relationship between users and electricity consumption. However, electricity consumption arising from building electrical appliance usage has its own specificity, as its consumption behavior is not influenced by the number of users and their behavior. This is because the usage of electrical appliances related to the building continues even when there are no users present, such as lighting usage.

According to Sun & Hon (2016), user
the model, represented through closed loops. These feedback loops indicate the cause-and-effect relationships between variables, as depicted in the causal loop diagram of the electricity consumption system shown in Figure 1.

The causal loop of clinic electricity consumption explains that the relationship between variables is additive. Each user's electricity consumption is an accumulation of the electrical usage of each individual electrical device. The electricity consumption of each user determines the clinic's electricity consumption. The greater the electrical usage from each user behavior, the greater the value of the clinic's electricity consumption.

Modeling clinic electricity consumption based on user behavior employs several assumptions to simplify the complexity of the real system. Nonetheless, the model still aims to maintain accuracy between the model and the actual system. The assumptions used in constructing the clinic energy consumption model are as follows:

1. The model does not experience extreme conditions, such as a drastic increase in the number of patients beyond the usual.
2. The duration for each patient's service

is similar.

3. Clinic electricity consumption is based on the average electrical usage of all user behavior.

Before conducting simulations, the logical representation of the model must be transformed into a Stock Flow Diagram (SFD), which provides the mathematical framework for the entire model's operation. The SFD is a flowchart that illustrates the working mechanism of the model when operated using Powersim language.

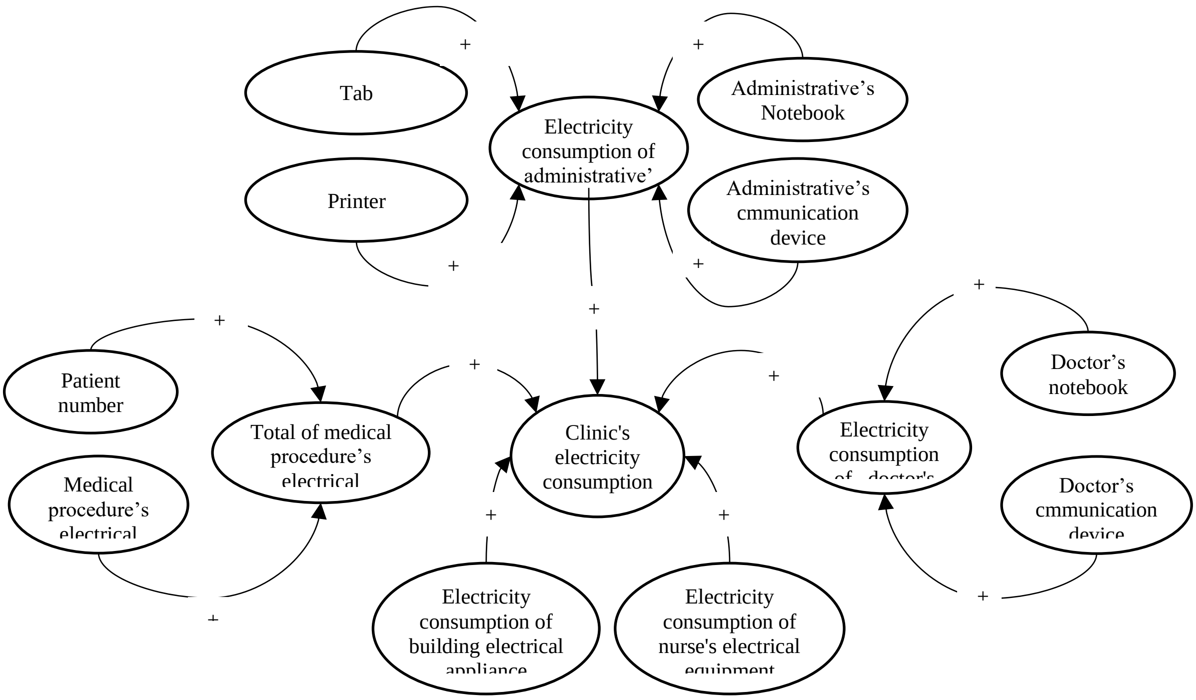

Figure 1.
Causal Loop Diagram for Clinic Electricity Consumption.

The next step in using the dynamic system model involves converting the logical construction shown in the SFD into mathematical constructions for simulation. The equations of the dynamic system model in this study were translated into Powersim language. Powersim language serves as a standard language for writing system dynamic simulations, making it easier to understand and simplify the conversion process from logical construction to mathematical framework.

Generally, electricity consumption estimates are based on past trends to analyze the required amount of electrical energy, allowing comprehensive and integrated planning considering future situations and conditions.

The electricity demand model is represented by the daily electricity consumption. The representation of the model is created using the Stock Flow Diagram based on the Causal Loop Diagram, as illustrated in Figure 2. Simulation parameters used in this simulation are shown in Table 1.

Table 1.
Simulation Parameter

Simulation Parameter	
Parameter	**Value**
Duration	1 month
Medical procedure electrical consumption	2.286 kWh/day
Building electrical consumption	4.561 kWh/day

3.3. Data Collection and Process

The Powersim model equations require relevant data to enable calculations. A series of data collection processes from the clinic have been conducted through questionnaires, interviews, and observations. The obtained data is then processed based on their respective behaviors. Based on observations and interviews with users and the equipment used, various usages are categorized according to users. Electrical equipment related to the building is not affected by user presence or activities, so the electricity consumption remains consistent according to the usage needs of these electrical appliances. For instance, outdoor lights are used during the evening, night, or in dark weather conditions.

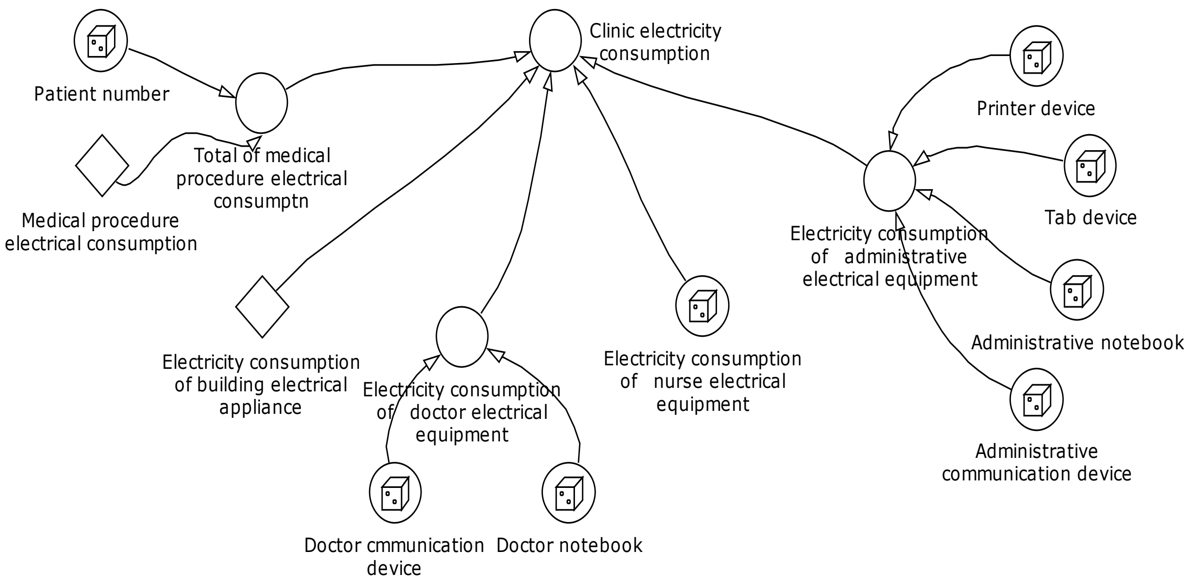

Figure 2.
Clinic Electricity Consumption Model

The overall electrical appliances related to the building are summarized and their electrical specifications and daily usage durations are calculated. There are nine types of electrical appliances related to the building. Since the consumption of electrical appliances related to the building is not influenced by the number or behavior of users, its consumption tends to remain stable. Therefore, the electricity consumption related to the building is classified as constant. The electricity consumption by the building is found to be 4,561 kWh/day.

Electrical appliances related to patients are affected by patient presence and activities, resulting in electricity consumption only when these appliances are used by patients. The electrical appliances related to patients are summarized and their electrical specifications and daily usage durations are calculated. Since the consumption of medical procedures is affected by patients' usage behavior of electrical appliances, its consumption varies according to the patients' usage. The consumption of electricity for medical procedures is only related to the electrical appliances used for medical purposes. Patients come when they receive medical treatment and leave immediately after the procedure. Seven electrical appliances are used by patients during medical procedures. The electricity consumption for medical procedures is found to be 1,988 kWh per patient.

Electrical appliances related to doctors are affected by doctor presence and activities, resulting in electricity consumption only when these appliances are used by doctors. The electrical appliances related to doctors are summarized and their electrical specifications and daily usage durations are calculated. Since the consumption of doctor's equipment is affected by doctors' usage behavior, its consumption varies according to the doctor's usage habits. Doctors only use two electrical appliances and not for extended periods. Doctors' time is primarily used for medical procedures and consultations with patients. The electricity consumption by doctor's equipment is found to be 0.059 kWh.

Electrical appliances related to nurses are affected by nurse presence and activities, resulting in electricity consumption only when these appliances are used by nurses. The electrical appliances related to nurses are summarized and their electrical specifications and daily usage durations are calculated. Since the consumption of nurse's equipment is affected by nurse behavior, its consumption varies according to nurse usage. Nurses only use one electrical appliance, which is a communication device, and not for extended periods. Nurses' time is primarily used to assist doctors during medical procedures and consultations with patients.

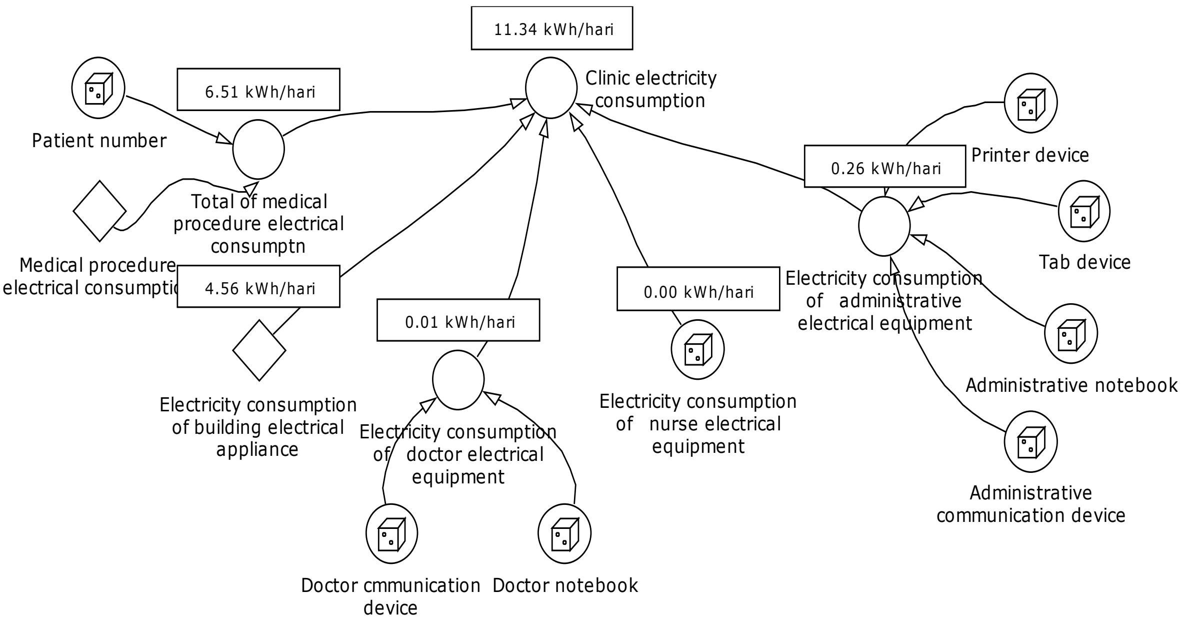

Figure 3.
Simulation of the clinic's energy consumption model

The electricity consumption by nurse's equipment is found to be 0.018 kWh. Electrical appliances related to administration are affected by administrative presence and activities, resulting in electricity consumption only when these appliances are used by administrators. The electrical appliances related to administration are summarized and their electrical specifications and daily usage durations are calculated. Since the consumption of administrative equipment is affected by administrative behavior, its consumption varies according to administrative usage. The electricity consumption by administrative equipment is related to administrative activities, including registration, payment, data recording, and medical records. Administrators use four electrical appliances in their clinic-related activities. The electricity consumption by administrative equipment is found to be 0.150 kWh.

4. Simulation

4.1. Model Simulation

The calculation was conducted using a single scenario, namely the business-as-usual scenario. The previously developed model was employed for this purpose. The relevant data were input into the model according to its behavioral characteristics. The model dynamically changes in accordance with user behavior as presented in Table 2. The simulation is conducted over a one-month period and repeated three times due to the limited availability of actual electricity consumption data. Each simulation will then be compared to three months of actual electricity consumption data. The data of users' electricity consumption and their electricity usage behavior are input into the model for calculation. Figure 3 illustrates the results of the model after the calculations are performed. The calculations depict the electricity consumption results for each user type. The advantage of the dynamic system is its ability to calculate the model's behavior dynamically. As a result, variations in simulation outcomes can be demonstrated depending on the provided data and formulas. This is something expected because achieving an ideal stable state in real conditions can be difficult. Figure 4 illustrates the fluctuations in electricity consumption as a result of the calculations performed.

Table 2.
User Behavior In Electricity Consumption

Users Behaviour	
User	**Behaviour**
Doctor's electrical equipment	Using two electrical devices with usage durations ranging from zero to one hour. Engaging more in activities related to medical procedures.
Nurses's electrical equipment	Using one electrical device with usage durations ranging from zero to one hour. Engaging more in activities related to medical procedures while assisting doctors.
Admin's electrical equipment	Using four electrical devices with varying durations among the devices, including using a mobile phone for 1-3 hours, using a tablet for 2-4 hours, using a printer for 0-1 hour, and using a laptop for 2-5 hours.
Medical procedure equipment	Using up to seven devices during procedures with durations ranging from 0.25 to 1 hour for each electrical device.
Building electrical appliance	Comprising 25 electrical devices that are used. Electricity consumption is constant and not influenced by user behavior.

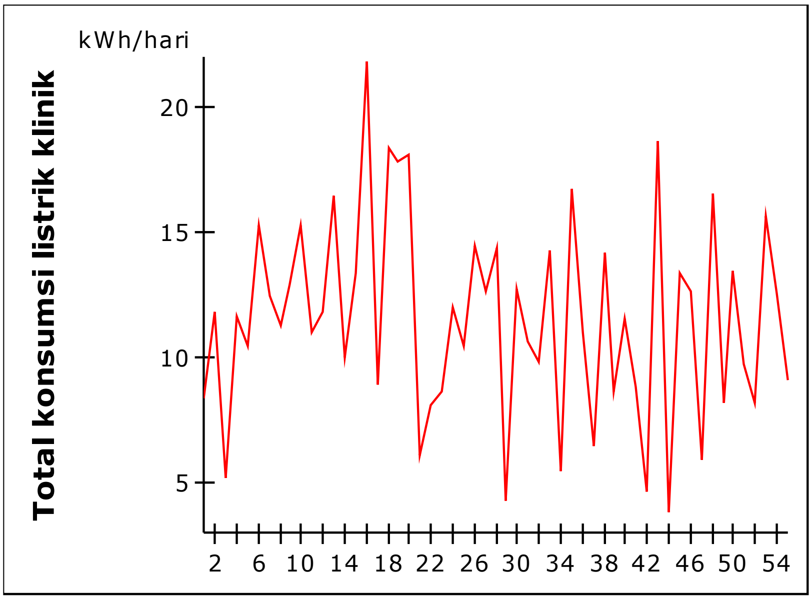

Figure 4.
Clinic Electricity Consumption Calculation Results

4.2. Model Validation

The similarity of the model with the real system is demonstrated by how well the calculation data can mimic statistical data and actual information. Therefore, validation is conducted on the built model, which can be done, among other methods, using performance or output model validation tests. Performance validity aims to obtain confidence in how well the model's performance aligns with the real system's performance, thus meeting the criteria for a scientific model. This validation is carried out by comparing empirical data with calculation results to assess the extent to which the output behavior of the model corresponds to the behavior of empirical data.

Validation testing is performed using MAPE (Mean Absolute Percentage Error) as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

Where:
At = Actual value at period t
Ft = Forecasted value / Calculation result at period t

According to Lewis (1982), the MAPE value can be interpreted into four categories, which are:

• <10% = very accurate
• 10% - 19% = good
• 20% - 49% = acceptable
• 50% or more = not accurate

Before performing validation, model verification is also conducted. The model is verified through visualizing the modeling process. It has been ensured that all variables function according to the given scenario so that calculations can proceed smoothly and yield accurate results.

The actual data used in this validation test comes from the monthly token filling for the clinic, which is then converted into kWh. Subsequently, matching is done based on the token filling days and working days during token electricity usage. Table 3 presents the validation data and the results of the error testing.

Table 3.
Clinic Electricity Consumption Calculation Results Validation.

	Workday (Day)	Actual (kWh)	Simulation (kWh)	MAPE
Recharge 1	30	326.6	355.19	8.75%
Recharge 2	31	335.6	343.00	2.21%
Recharge 3	33	335.6	328.69	2.06%

The error testing indicates the comparison between simulated kWh and actual kWh. Error testing has been performed on three sets of actual data, revealing that the resulting errors are between 2% and 8%. Utilizing the categorization defined by Lewis (1982), the simulation results fall into the "very accurate" classification. The model's performance is evaluated using two additional metrics: RMSE (Root Mean Square Error) and MAE (Mean Absolute Error). RMSE measures the average magnitude of the error between predicted and actual values, yielding a value of 17.51 in this case. MAE represents the average magnitude of errors in a set of predictions, with a value of 14.30 here. These metrics help assess how well the model predicts outcomes compared to the actual data.

The results of the calculation process need to be tested for their sensitivity to determine how well the model provides consistent results with changes in parameters. According to Ciampi et al. (2018), sensitivity testing can be conducted by varying parameter values and comparing the results. In this study, the parameter that has the greatest influence on electricity consumption is patients. Therefore, a 10% change in the parameter of medical procedure electricity consumption was applied. The sensitivity value of the model obtained was 8.94%, indicating that the model is sensitive to parameter changes. This demonstrates the model's stability in responding to variations in parameters, effectively adjusting results within the altered parameter range.

5. Findings and Discussion

The results shown in Figure 4 indicate that electricity consumption at the clinic varies significantly each day. While electricity usage is minimal today, it can become substantial or even reach a high peak on the following day. Judging from consumption stability, the behavior of building consumption, although the highest, does not influence these variations. The electricity consumption value of building-related equipment remains relatively constant, whether there are many users or none at all. Building electricity usage follows the pattern of user activity, such as indoor lighting being used only in the evening and at night.

The electricity consumption by doctors exhibits varied results, even though doctors use only two electrical devices. On the other hand, doctors spend most of their time on medical procedures and consultations with patients, resulting in relatively low electricity consumption. Similarly, the electricity consumption by nursing equipment also varies, but only one device, which is a communication tool, is used. Additionally, the time spent at the clinic is dominated by assisting doctors in procedures and conducting consultations, leading to relatively low electricity consumption by nurses.

Administrative staff use multiple electrical devices, leading to higher usage variation. Furthermore, the duration of device usage is directly linked to the number of patients. As the number of patients increases, administrative activities also rise. This is due to administrative staff managing patient-related tasks beyond medical procedures, such as registration, payments, and data handling. Administrative staff also assist patients seeking consultation about clinic services over the phone or through chat. As a result, administrative equipment contributes significantly to electricity consumption compared to other users.

Patients represent the highest electricity consumers. Treating a single patient requires the use of seven electrical devices with a considerable combined power. Moreover, dental procedures often demand a significant amount of time for a single dental service. If a patient requires multiple dental treatments or chooses more than one service, such as teeth cleaning and multiple fillings, the procedure duration and electricity consumption increase accordingly. This makes patients the largest electricity consumers among all users, as illustrated in Figure 5.

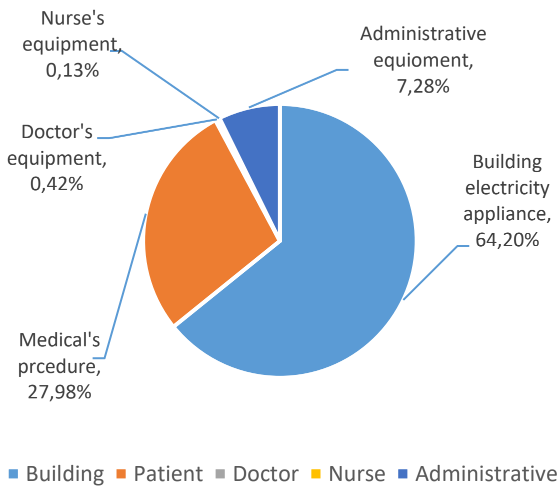

Figure 5.
User Contributions to Clinic Electricity Onsumption

The electricity consumption for medical procedures is very high for a single individual, especially when there is a large number of visiting patients. This leads to significant variation in electricity consumption as it is greatly influenced by the number of patients requiring medical procedures. Figure 6 displays the variation in the number of patient visits each day. As electricity consumption from medical procedures contributes the most to the overall consumption, the uncertainty in the number of patients has a substantial impact on the clinic's electricity consumption variability.

Another uniqueness of patients is their quantity, which can influence the electricity consumption of other users. When the number of patients increases, the administrative tasks also increase as they need to manage more patients. Thus, the relationship between the number of patients and the electricity consumption of administrative equipment is positively linear. In contrast, for doctors and nurses, the number of patients has a negative impact on the electricity consumption of their equipment. With more patients, doctors and nurses spend more time on medical procedures, resulting in reduced usage time for their personal electrical devices.

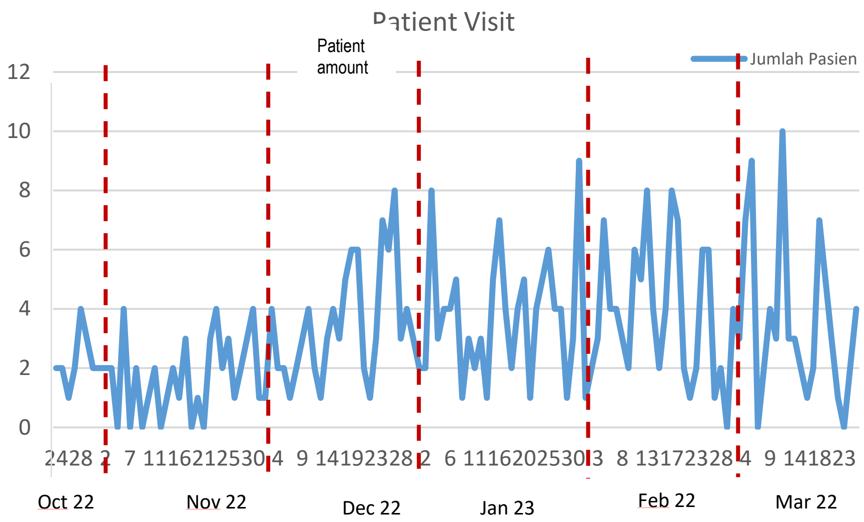

Figure 6.
Number Of Patient Visits

Choosing the right solar panels to meet the daily energy needs of a clinic is a crucial step in supporting sustainability and operational efficiency. Through simulation, we can gain a deep understanding of the clinic's daily energy consumption patterns. This simulation enables us to identify and estimate the daily energy demand, considering variations in clinic activities such as medical equipment usage and lighting. Accurately knowing the energy requirements through simulation allows decision-makers to make more informed choices in selecting appropriate solar panels.

The knowledge gained from simulation also provides a clearer picture of the type and capacity of solar panels needed to optimally meet the clinic's daily energy needs. This not only enhances energy efficiency but also ensures operational reliability. By choosing the right solar panels, the clinic can reduce dependence on energy supply from the public grid, lower long-term operational costs, and make a positive contribution to the environment by reducing carbon footprint.

Furthermore, the insights gained from simulation enable the clinic to plan long-term investments in sustainable energy infrastructure. By selecting appropriate solar panels, the clinic can optimize their investment in renewable energy technology, enhance operational sustainability, and reduce environmental impact. Thus, a thorough understanding of daily energy needs through simulation is key to selecting the best energy solutions for the clinic, creating a more sustainable and energy-efficient working environment.

5. Conclusion

The research findings demonstrate that electricity consumption varies significantly due to its strong correlation with the number of patients requiring medical procedures. The simulation indicates that the clinic's electricity consumption ranges from a minimum of 3 kW/day to a maximum of 24 kW/day during high peak times, with a daily average of 11 kW/day. The accuracy of the model is confirmed through the MAPE method, resulting in errors ranging from 2% to 8%, categorizing it as a highly accurate model. Electricity consumption is a key criterion in the selection of solar panel technology.

User behavior significantly influences the consumed energy amount. The energy consumption model can effectively estimate daily electricity consumption by categorizing behaviors into five types: building equipment usage behavior, doctor equipment usage behavior, medical procedure electricity usage behavior, nurse equipment usage behavior, and administrative equipment usage behavior. Moreover, the consideration of different user types enhances the model's ability to predict user electricity consumption. The dynamic user behavior ensures that the simulation approximates real-world conditions. By accurately knowing the actual daily energy consumption, the selection of solar panels is expected to be more suitable.

Based on the conducted analysis, several recommendations can be provided as managerial implications of this research, including:

1. There is a strong correlation between users' electricity usage behavior and overall electricity consumption, as indicated by the high accuracy values. Clinic owners or decision-makers need to establish regulations regarding electricity usage in the clinic, ensuring that usage remains organized and controlled.
2. It is important to promote energy-saving behavior by using electrical devices only when necessary. Employees should remind each other to use electricity conservatively, and decision-makers should conduct regular training and evaluations to enhance awareness of wise electricity consumption.
3. Patient scheduling can be better organized and optimized to maintain more stable electricity usage, particularly for medical equipment, thereby impacting medical device electricity consumption.

This study is limited to three out of five usage behaviors. Future research could include all five usage behaviors to provide a more comprehensive simulation result. Implementing the study in a wider range of locations and involving more devices could also yield more representative results. Additionally, future research could explore alternative methods, such as utilizing data mining techniques, to simulate energy consumption.

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