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Doctoral Dissertation

Base Transceiver Station Archetype-Based
Modeling of Energy Demand and Analysis of
Renewable Energy Integration for
Telecommunication Networks

MOCHAMAD MARDI MARTA DINATA

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Graduate School of Engineering,

The University of Osaka

Division of Sustainable Energy and Environmental Engineering

Abstract

The growing demand for digital services and video streaming has increased wireless broadband traffic, leading operators to upgrade their Base Transceiver Stations (BTSs) cellular networks infrastructure. Energy optimization is essential for maintaining efficiency amidst this growth and rising energy costs have heightened interest in green solutions. The integration of Hybrid Renewable Energy Systems (HRES) into is a promising strategy for advancing the clean energy transition and sustainability while boosting efficiency. Telecom operators face challenges due to limited tools for comprehensive demand and supply studies in green power generation. There is a lack of macro-level frameworks to assess energy demand in cellular networks as a tool for energy monitoring, that utilizes bottom-up information from BTS site representations and stock composition variations. Moreover, current research on the supply side is limited to small-scale BTS site samples, overlooking spatial constraints and macro-level feasibility. This absence of a scalable HRES integration framework creates uncertainty for telecom operators, hinders effective implementation. This dissertation addresses these gaps by developing a macro-level energy demand assessment framework that uses bottom-up BTS site information to reflect real operational conditions better. Established building-sector assessment methods are adapted to define BTS site archetypes by system configuration, deployment type, and spatial characteristics. Then, the analytical framework is enhanced by incorporating municipal-level BTS site stock compositions that capture socioeconomic variations and archetype-based BTS site-level energy demand estimates. On the supply side, a modeling framework was developed to construct HRES archetypes using data from a synthetic stock model, accounting site characteristics, renewable potential, and spatial constraints. A techno-economic analysis identified HRES archetypes that outperform existing BTS site electrification systems based on their spatial distribution and renewable energy resources. The dissertation is comprised of six chapters whose summary is explained as follows:

Chapter 1 outlines the current approach of energy demand modeling for cellular telecom network, global clean energy transition targets and highlights the telecom sector's role in supporting them, including ongoing efforts to integrate hybrid renewable energy systems into cellular networks.

Chapter 2 establishes the initial stage for macro-level energy-demand evaluation in cellular networks, comprising four steps: segmentation, characterization, quantification, and aggregation. Physical and technical characteristics capturing local BTS site features are used to develop archetypes and 24-hour power-factor profiles. These archetypes provide reference models for

data-limited regions with similar site characteristics.

Chapter 3 presents an enhanced energy-demand modeling framework for cellular networks that quantifies energy demand at the BTS site stock level. It captures the composition and spatial variation of BTS site types, as well as the socio-economic factors of the region. This framework improves understanding of BTS site stock composition and energy demand characteristics, providing valuable insights for HRES implementation.

Chapter 4 presents a scalable framework for implementing HRES within cellular telecommunications networks while ensuring economic feasibility. Calculating the energy generation potential of HRES and its evaluation in meeting the demands of the cellular network are demonstrated. For the telecom industry, this study serves as a reference for integrating HRES into its networks.

Chapter 5 provides an integrated discussion to highlight the findings, methodological contribution and applicability of the proposed frameworks.

Chapter 6 provides the conclusion of this dissertation related to formulated research objectives.

Ultimately, the HRES integration aims to enhance the overall revenue of telecom operators by improving the energy efficiency and reducing energy costs, participating in efforts to meet the Indonesian government's energy transition target.

List of Publications

Journal Articles

- 1) M. M. M. Dinata, Y. Yamaguchi, H. Uchida, Y. Shimoda, and A. Subekti, “Macro-level bottom-up energy demand modeling for telecommunication networks,” IEEE Access, vol. 12, pp. 127198–127211, 2024, doi: [10.1109/ACCESS.2024.3434976](https://doi.org/10.1109/ACCESS.2024.3434976).
- 2) M. M. M. Dinata, Y. Yamaguchi, H. Uchida, Y. Shimoda, and A. Subekti, “Macro-Level Energy Demand Model for Cellular Telecommunication Networks,” IEEE Access, vol. 13, pp. 144982–144994, 2025, doi: [10.1109/ACCESS.2025.3599587](https://doi.org/10.1109/ACCESS.2025.3599587).
- 3) M. M. M. Dinata, Y. Yamaguchi, H. Uchida, Y. Shimoda, and A. Subekti, “Scalable Integration of Hybrid Renewable Energy System for Cellular Telecommunication Networks,” IEEE Access, vol. xx, pp. xx, 2025, doi: xx. (under review)

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Abbreviation List

BTS	Base Transceiver Stations
CDF	Cumulative Distribution Function
COE	Cost of Energy
CRF	Capital Recovery Factor
DG	Diesel generator
DU	Dense urban
GHI	Global Horizontal Irradiance
GIS	Geographical Information System
HRES	Hybrid Renewable Energy Systems
IBS	In Building System
ICT	Information and Communication Technology
MH	Micro Hydro
MIMO	Multiple-Input Multiple-Output
NE	Network Element
NPC	Net Present Cost
O&M	Operation & Maintenance
PV	Photovoltaic
R	Rural
RSU	Road Side Unit
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SU	Suburban
U	Urban
WT	Wind turbine

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1 Introduction

1.1 Background

The telecommunication industry supports communication networks and serves as the backbone of the global digital revolution. The number of mobile subscribers worldwide increased by 7.9 billion in Q1 of 2019 [1] and is expected to reach 8.9 billion by the end of 2025 [2]. The digitalization of almost all aspects of modern life has considerably increased the number of smartphone subscriptions and average data volume per subscription [3], requiring telecom operators to expand and strengthen their networks through base transceiver station (BTS) deployment to prevent network congestion. This expansion has significantly increased operational energy demand and cost, with energy expenses accounting for roughly 20% of total operational expenditure [4]. The network spans from the head-end gateway mobile switching center to the BTS layer, where BTS sites—responsible for transmitting and receiving mobile signals—consume approximately 57% of total network power [5]. Further projections show that the global Information and Communication Technology (ICT) sector energy demand is projected to reach 1,752 TWh/year by 2030 [6], which is approximately 2–3% of global energy demand and approximately 2.5–4% of global carbon emissions [7]. As network expansion continues to drive energy consumption, telecom operators must focus on improving energy efficiency to mitigate rising operational costs and declining profitability from legacy services.

McKinsey & Company stated that telecom operators can potentially achieve 30% network energy cost savings by sourcing or generating renewable energy [8]. A promising approach is the integration of green energy into the BTS network using a hybrid renewable energy system (HRES) that combines multiple renewable resources, such as solar PV, wind turbine, hydropower, gas turbine, fuel cell, diesel generator (DG), and battery, into the BTS site [9]. HRES implementation requires careful design across technical, economic, environmental, and social aspects. According to Kaur et al. [10], HRES with the optimal configuration can supply electricity at 0.12 \$/kWh, cheaper than that of conventional DG-powered BTS in off-grid rural areas. Conversely, on-grid sites may be viable if the electricity rate exceeds \$0.25/kWh [11]. However, integrating HRES into existing telecom networks is challenging because of the need to supply electricity to BTSs operating with intermittent renewable energy sources. According to the report of the GSM Association [12], only seven telecom operators worldwide—primarily based in Europe—operate entirely on renewable energy. However, in developing countries, as in Asian and African regions, no telecom operator has implemented HRES across the entire network; moreover, the implementation is limited to pilot projects and research and development efforts.

These challenges and opportunities are particularly relevant to Indonesia, which has committed to achieving 100% renewable energy by 2060 [13]. The fourth-generation BTS cellular networks, which is the dominant technology for high-speed cellular connectivity services in the telecommunications sector, must also be adapted to achieve this goal. Cellular networks in Indonesia

accounted for roughly 2% of national electricity use in 2022 [14], and annual network expansion rate is projected to be ~20% by 2029 [15]. With BTS networks representing the majority of telecom energy consumption, enhancing BTS energy efficiency and expanding renewable integration are essential components of the sector's transition strategy. Although HRES has the potential to reduce costs and emissions, its widespread adoption will require improved modeling, planning, and evaluation frameworks to support reliable and cost-effective deployment.

1.2 Literature Review

This section mainly consists of three sub-sections based on the research stages in this study. Section 1.2.1 outlines the studies related to the development of a macro-level energy demand assessment framework based on bottom-up information from BTS sites. Section 1.2.2 examines the enhancement of the macro-level energy demand model for cellular telecommunication networks. Section 1.2.3 summarizes the studies related to the scalable integration of HRES for cellular telecommunication network.

1.2.1 Macro-Level Bottom-up Energy Demand Modeling for Telecommunication Networks

There are several established methods to assess the energy demand of the telecommunication networks. The first method for estimating the power consumption of BTSs, uses historical electricity demand data called the top-down method. Etoh et al. [16] used NTT Docomo's total equipment power consumption data to estimate the power consumption for 25,000 BTS sites in Japan. They calculated the daily power consumption for 52 million users by considering factors such as the power usage effectiveness index and power consumption for various network elements. Van Heddeghem et al. [17] collected the global annual power consumption data categorized by activity and subscription type from 11 telecom operators to estimate the average power consumption per mobile and fixed-line subscriber. The global power consumption of telecommunication networks from 2007 to 2012 was quantified by multiplying these values by the ratios of a representative sample and summing the results. Lundén et al. [18] conducted a similar analysis to estimate European telecommunications networks' annual electricity consumption and carbon emissions based on survey data collected from 15 operators. The methodology utilized in these studies assumes that each BTS exhibits a uniform profile. The approach divides aggregate energy consumption proportionally, contingent upon the number of BTS in operation.

The second method is to measure the BTS power consumption remotely or directly using an ampere plier. A new site power consumption assessment document from Ericsson [19] describes the method to assess the power consumption of one BTS by directly measuring the power consumption for each electricity connection using an ampere plier. Each value is then converted into a power unit and aggregated to calculate the total power consumption of the BTS. This grained-coarse method

provides a detailed representation of BTS characteristics, but is resource- and time-intensive and difficult to cover the BTS stock.

The third method is an engineering bottom-up approach. Deruyck et al. [20] and Alsharif et al. [5] quantified the power consumption of a BTS as the sum of the modeled power consumptions of all BTS components, including load-independent (air conditioners, microwave link, and rectifier) and load-dependent (baseband, transceiver, power amplifier, and antenna) equipment. In both studies, the information from the data sheets of various network equipment manufacturers and interviews of private operators were considered. The power consumption of only one sample was then multiplied by the number of estimated BTSs to calculate the total power consumption in the region. However, most of the data used is confidential and not generally available. In addition, extrapolation of a small number of BTS samples to represent the entire network may be erroneous.

1.2.2 Macro-Level Energy Demand Model for Cellular Telecommunication Networks

Chen et al. [21] categorized the methods for estimating energy demand in telecommunication networks into three primary groups according to the level of detail in the measurement information, namely, top-down assessments, coarse-grained methods, and bottom-up aggregation methods, with the complexity increasing with increasing detail.

Top-down assessments only require the overall network or platform power consumption. Van Heddeghem et al. [17] analyzed the global annual power consumption of 11 telecommunications operators and calculated the average usage per mobile and fixed-line subscriber. They also estimated the global telecommunication network consumption from 2007 to 2012 by scaling these averages with sample ratios. Similarly, Lundén et al. [18] evaluated the annual electricity usage and carbon emissions of European networks, using data from 15 operators and assuming uniform BTS profiles. Etoh et al. [16] divided NTT Docomo’s annual power consumption into consumption per user and consumption of its 25,000 BTSs. Although these studies offer insights into historical energy consumption, they do not consider the stock composition and detailed representation of BTS sites.

Bottom-up component aggregation methods focus on micro- or site-level power consumption. Auer et al. [22] developed a 4G BTS power and traffic model, detailing power consumption across components such as power amplifiers, radio frequencies, basebands, DC–DC power supplies, active cooling, and AC–DC units. This aggregated consumption informed a traffic demand model that accounts for spatial and temporal variations in mobile subscribers to assess a cellular network’s energy efficiency. Kuaban et al. [23] extended this by modeling the energy consumption of BTS sites, including fronthaul, backhaul, air conditioning (indoor BTS), and auxiliary equipment (e.g., lighting and security). However, this energy demand approach is suited only for analyzing individual BTS sites or small networks. Its highly “local” nature limits the model’s ability to generate network-wide

aggregation results with sufficient sample representations and details, thereby limiting the model's ability to break down results into more granular levels, which could be valuable for further analyses.

Coarse-grained methods quantify the energy demand of BTS site stock by integrating the power consumption measurement of a group of equipment that performs similar operations at BTS sites and the information on BTS site stock. Ericsson [19] reported a measurement integration method to evaluate the total power consumption of all equipment groups across three BTS sites. Phillips et al. [24] analyzed the electricity consumption of telecommunications equipment using data from 3,918 central offices of a major U.S. telecom provider. Ibrahim et al. [25] collected >4,000 BTS samples in Zurich to compare energy efficiency using the energy consumption gain metric for 2G, 3G, and 4G equipment. Although this coarse-grained approach enables macro-level energy analysis, it has two key limitations. First, prior studies assumed uniform power consumption across all BTS site types, without assessing whether each site type has distinct physical, technical, and energy demand characteristics. Second, these studies neglected spatial variation in BTS site stock, relying on energy demand data from a sampled region and extrapolating it to the broader network, thereby overlooking important regional differences. However, as shown in this study, the number of BTS sites and the composition of the site type vary considerably spatially.

1.2.3 Scalable Integration of Hybrid Renewable Energy System for Cellular Telecommunication Networks

Over the past two decades, several studies have explored integration of renewable energy into telecommunication networks. Devela et al. [9] analyzed the global HRES implementations incorporating photovoltaic (PV), wind, hydropower, gas turbines, fuel cells, diesel generators, and batteries. Their analysis considered key technical, economic, environmental, and social factors, as well as whether the system operates independently (off-grid) or is grid-connected (on-grid). Alsharif et al. [26] developed a sustainable solar energy system for off-grid cell sites in Egypt, highlighting PV systems as an effective choice for wireless operators. Kuaban et al. [23] analyzed the performance of off-grid BTS sites, which are affected by energy storage variations. Asghar et al. [27] investigated the techno-economic feasibility of off-grid solar-powered BTS sites under varying climate conditions. They demonstrated the influence of the battery type, fuel price, and location on the system performance and cost-effectiveness.

For on-grid telecom sites, Devala et al. [28] analyzed the optimum design and evaluated the economic performance of HRES for 25 BTS site locations with variations in the grid outage duration. Ali et al. [29] provided a techno-economic analysis and practical and policy recommendations on the utilization of clean energy from 15 HRES BTS site locations to support a fast electric-vehicle charging station. Wijesinghe [30] emphasized the need for government support, such as incentives and tax exemption, to ensure profitability in the implementation of HRES. Rizqiawan et al. [31] discussed the

economic aspect analysis of PV HRES development for 11 BTS sites in Indonesia, highlighting the importance of considering space availability constraints.

These assessments demonstrate that integrating HRES as the BTS site energy supply reduces grid electricity purchases and significantly decreases DG operating hours. Additionally, significant OPEX savings and increased energy reliability could be obtained. However, most HRES analyses are confined to small-scale studies, with no framework scalable to a regional- or national-level assessment. The HRES design may not be applicable to other regions owing to insufficient data for developing an HRES design that represents the BTS site network and its renewable potential. Furthermore, previous studies fail to consider the actual availability of BTS site space, types, and deployments that are suitable for HRES.

On the demand side, the methods are categorized into three primary groups corresponding to the level of data resolution, i.e., top-down assessments, coarse-grained methods, and bottom-up aggregation methods, where the complexity increases with increasing detail [21]. Among the three methods, the coarse-grained approach is well-suited for large-scale applications as it quantifies the energy demand of the BTS sites by aggregating the power consumption profiles of functionally similar equipment with BTS site stock data [24], [25]. They addressed the distinct physical, technical, and spatial variations, along with the energy demand characteristics of the BTS site stock, based on regional socioeconomic factors.

1.3 Research Gap

After reviewing and analyzing the weaknesses of the approaches, we identified gaps in research concerning energy demand and the integration of renewable energy in telecommunication networks. The energy demand models produced should be capable of 1) providing a standardized method for accurately estimating the energy demand of telecommunications networks, regardless of the region. 2) quantifying the energy demand at the BTS site stock level, 3) representing the BTS site stock composition for various BTS types and their spatial variation, and 4) representing the physical and technical characteristics of BTS sites.

In terms of the integration of renewable energy supply, the frameworks must be capable of 1) assessing the energy demand and supply-balance of the BTS sites at the site-level, scalable up to the national level (macro-level). 2) evaluate the characteristics of the BTS sites profile to develop an HRES design that aligns with regional renewable energy potential and geographical conditions, while considering space availability for installations. 3) represents the HRES design for various BTS site deployment types with confirmed technical and economic viability.

A framework that incorporates such features provides valuable insights into the spatiotemporal characteristics of energy demand and supply at a granular resolution. The developed framework

should also apply to regions with limited data availability. This study proposes a framework that satisfies these requirements.

Currently, no framework exists to evaluate the balance between energy demand and supply for a BTS site when renewable energy is integrated, scalable from the site to the national level. Most existing research focuses on few BTS sites, often overlooking spatial constraints and space availability. Furthermore, the lack of analysis at the macro scale introduces uncertainty regarding the extent to which HRES contributes to energy efficiency. Prior to integrating the system, telecom operators must have a clear understanding of the energy that HRES can supply and its advantages over the existing electrification system. Insufficient analysis of the geographical limitations and economic performance further complicates the implementation efforts. This restricts telecom operators from integrating HRES into their cellular networks.

1.4 Aim and Objectives

The main aim of this dissertation is to develop reliable energy-demand modeling methods for cellular telecommunication networks and to integrate these models with renewable energy resources, using parameters that can serve as a reference for all regions, particularly data-limited areas such as developing Asian countries. It addresses the absence of a comprehensive framework that captures BTS site stock composition, spatial distribution, and the physical and technical characteristics that shape energy-demand behavior. In addition, it advances macro-level HRES implementation analysis by developing a scalable framework for integrating HRES generation supply with the energy demands of BTS site networks, from the individual site level to the national scale. To achieve these aims, we have formulated the following research objectives.

- 1) To develop a foundational, scalable, and reliable macro-level energy demand modeling framework for cellular telecommunication networks that incorporates socio-economic factors influencing network stock composition, enabling applicability across regions with similar characteristics.
- 2) To develop an HRES design framework that integrates geographical and meteorological conditions, along with spatial constraints and BTS sites characteristics, and to assess the techno-economic performance and potential renewable energy contributions of integrating HRES into cellular telecommunication networks.

1.5 Contributions

This dissertation resulted contributions to the literature through the BTS site archetype-based modeling of energy demand and analysis of renewable energy integration for telecommunication networks. First, it introduces a macro-level energy demand modeling framework for cellular telecommunication networks that addresses the limitations of conventional approaches outlined in subsection 1.2. Second, it enhances the understanding of the composition of BTS site stock in Indonesia, including its spatial distribution and energy demand characteristics, offering valuable

insights for developing regions, particularly in Asia. Third, it presents a scalable framework to implement HRES within cellular telecommunications networks while ensuring economic feasibility, demonstrating both energy generation potential of HRES and its effectiveness in meeting the cellular network's demands. Finally, this study offers a practical reference for telecom operators for integrating HRES into their networks to enhance telecom operators' overall revenue through improved energy efficiency and reduced energy costs, while supporting national green energy transition goals.

1.6 Dissertation Outline

This dissertation consists of six chapters, which are outlined in Figure 1-1 and summarized as follows:

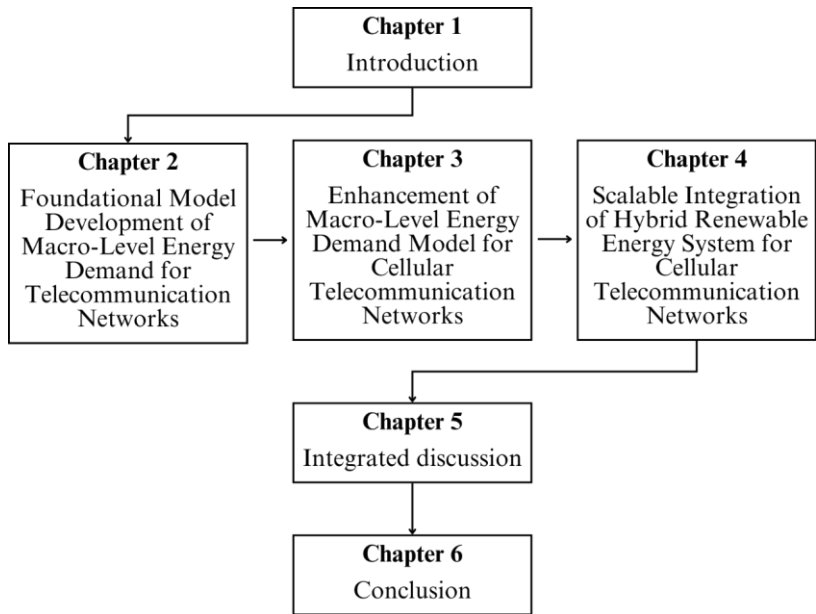


Figure 1-1. Dissertation outline

Chapter 1 reviews the conventional approach of energy demand modeling for cellular telecom network, global clean energy transition targets and underscores the telecom sector’s contribution to achieving them, including current initiatives to integrate hybrid renewable energy systems into cellular networks.

Chapter 2 outlines the initial development of an energy-demand model for cellular networks at the macro-level. The first step is to segment the sample dataset based on primary parameters to identify BTS site features. Second, develop archetypes and 24-hour power-factor profiles that reflect the physical and technical characteristics of the local BTS site. Each represents one BTS segment and is applicable to areas outside the sample region. The third step is to quantify the power consumption of each BTS segment, and lastly, aggregate power consumption and the proportion of BTS segments by regional BTS number, based on its density category.

Chapter 3 introduces an improved energy-demand modeling approach for cellular networks that measures energy consumption at the individual BTS site level. It accounts for the diversity and geographical distribution of BTS site types, as well as the region's socio-economic conditions. This

framework enhances understanding of the composition of the BTS site stock and the attributes of energy demand, providing essential information for HRES implementation.

Chapter 4 introduces a scalable framework for integrating HRES into cellular telecommunications networks while maintaining economic viability. The potential for HRES energy generation is assessed, along with its effectiveness in meeting the cellular network's energy requirements. This research acts as a point of reference for the telecom sector in incorporating HRES into its infrastructures.

Chapter 5 provides an integrated discussion to highlight the findings, methodological contribution and applicability of the proposed frameworks.

Chapter 6 provides the conclusion of this dissertation related to formulated research objectives.

2 Foundational Model Development of Macro-Level Energy Demand for Telecommunication Networks

2.1 Purpose

Comprehensive planning is critical for telecom operators to deploy HRES in their services. The planning begins by calculating the energy demand for the network to be served, which requires not only micro or site-level analysis but modeling considering the BTS characteristics of the entire network (macro-level analysis). To date, three different methods for estimating the power consumption of BTSs have been reported: historical or top-down approach, coarse-grained direct measurement approach and engineering bottom-up approach. Although these methods are useful, they are insufficient for the comprehensive planning of HRES for the BTS network. The top-down approach is inappropriate because HRES integration requires detailed consideration of the local conditions to reduce the risk of overestimating or underestimating power consumption. In addition, the total network power consumption is unavailable for all telecom operators, particularly in developing countries. The direct measurement method also requires significant resources and time owing to extensive variations of system configuration and widespread locations of BTSs. Researchers have found it difficult to construct detailed models for applying the bottom-up approach because of the limited availability of site profile information, including the power consumption of each BTS element. In addition, aggregating the performance of all BTSs in the entire network based on only one or a few samples is challenging and unconvincing.

This research aims to develop a method that can be applied to the regional conditions of telecommunication networks by focusing on three main objectives. First, it aims to establish reliable methods for modeling the BTS network energy demand using parameters that can serve as a reference for all regions, with particular emphasis on data-limited regions such as developing Asian countries. This study takes Bali, Indonesia, as a case study to demonstrate the proposed method. Bali was selected because its meteorological characteristics and data availability are representative of Indonesia and many other developing Asian regions. Second, the research establishes methods for macro-level evaluation while capturing the local characteristics of BTSs. Finally, it aims to develop a preliminary planning phase of the overall implementation framework for HRESs to ensure sufficient energy distribution between demand and renewable energy supply for the telecom network.

2.2 Methodology

2.2.1 Data Availability & Constraints

The main data in this research were obtained from the telecom site profile database and are listed in Table 2-1. The data were collected from a telecom operator in Indonesia in 2022 and were related to the BTSs serving their 4G network. For confidentiality purposes, the operator or site name is not

displayed in this paper. The data contain the site location, BTS type, system configuration, and peak power consumption of the sample BTSs.

Table 2-1. Data from telecom site profile database

No	Data collected	Detail
1	BTS coordinate	Longitude and latitude decimal degree format of 4G BTS samples (n=8527)
2	Location	Location of the samples, including the city/district name
3	System configuration	Detailed configuration of the BTS, including information about the used antenna, frequency, and bandwidth
4	BTS type	Information on the BTS types used for each sample related to cell coverage and deployment, including Macro, Micro, IBS, and pico
5	Peak power consumption	Maximum power consumption (kW) of each BTS sample

Figure 2-1 shows the location of the sample BTSs distributed in 314 Jakarta and West Java province districts. We identified the density category range of the districts, where the location of each sample belongs to the classification proposed by Hinton et al. [32]: Dense Urban (DU), Urban (U), Suburban (SU), and Rural (R), as shown in Table 2-2. To determine the density category, we used the population data from the official statistics bureau [18]. Table 2-2 shows the proportion of the BTS samples per category. Approximately 90% of the samples were located in dense urban and urban areas.

Table 2-2. Density category distribution

Density category	Density (people/km ²)	Proportion (%)
Dense Urban (DU)	>10,000	50.3%
Urban (U)	1,001–10,000	41.3%
Suburban (SU)	301–1,000	7.1%
Rural (R)	0–300	1.2%

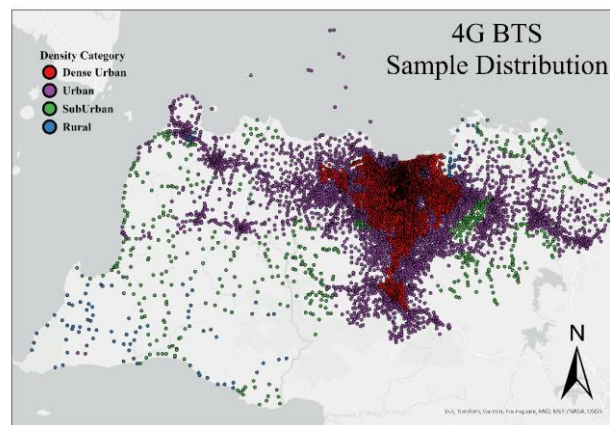


Figure 2-1. 4G BTS sample distribution from a telecom operator in Indonesia

The power consumption of each BTS is different and depends on the coverage area and the amount of traffic handled. The BTS cell coverage in the heterogeneous network has been explained by Sharma [33], as follows. BTSs are of four types, namely, macro, micro, pico, and femto. The BTS

location is designed to cover the entire population and facilities to support the activities in the service region. All BTSs transmit 360° signals, but the coverage area differs as the BTS type decreases from macro to femto. Macro BTS is used primarily, as it has the largest area coverage for up to 30 km within a cell radius. Many constraints cause cell coverage to be uneven, and the operator uses micro BTS to cover the blank spot. The same mechanism is used to determine the deployment of pico and femto BTSs with additional consideration of population density, geographical conditions, and social activities. The BTS types available in the database are macro, micro, pico, and in-building system (IBS). Instead of femto, the IBS term is used by telecom operators in Indonesia to represent the in-building coverage in the region. In regard to coverage, IBS uses a wall-mounted distributed antenna system, with the coverage of each antenna equivalent to that of a femtocell BTS. However, in terms of capacity, the IBS is equivalent to a macro BTS with a capacity of up to 2,000 simultaneous users.

In addition to coverage, operators must now use the maximum configuration of their equipment to meet very high data traffic demands. In dense areas, operators need to activate all three permitted frequencies in addition to the multiple-input multiple-output (MIMO) antenna configuration and bandwidth allocation, which also affect the traffic capacity that can be served. This can be illustrated as one BTS equipment transmitting three different signal layers simultaneously. System configuration relies on radio details from the site profile database, such as MIMO antenna configuration, used frequency, and allocated bandwidth for each BTS. Different equipment manufacturers and regional traffic demand result in various configurations. 1×1, 2×2, and 4×4 MIMO antenna configurations are available in our samples. The frequencies used for 4G base stations in the database are 900, 1800, and 2100 MHz, with bandwidths varying between 10, 15, 20, 25, and 30 MHz.

Table 2-3. Additional data collected

No	Data collected	Detail
1	BTS historical log file	-4-month historical log file of 4G BTS (n=4) from four locations representing different density categories -The log data contained information about BTS power consumption and broadband data traffic captured every 15 min for a 24 h period.
2	Population profile database	-District-level population information gathered from Indonesia's official statistics bureau -The information includes population, area, and density (people/km ²)
3	4G BTS network share	The total number of 4G BTSs in Indonesia was assessed from the annual reports of four telecom operators in 2022 [20-23]
4	GIS shapefile	District-level geographical information system (GIS) shapefiles of Indonesia for geographical analysis
5	Electricity sales	Electricity sales in 2022 in Indonesia, obtained from the Ministry of Energy and Mineral Resources

Table 2-3 lists the remaining data used in this study. We used the measurement data on traffic and power consumption, collected from four BTSs. As a validation, this study estimated the total

energy demand of the entire BTS stock in Indonesia. For this purpose, we used the total population of Indonesia collected from the official statistics bureau, which is 276 million.

This study had the following constraints:

1. The Indonesian telecom operator had dismantled all 3G equipment, with only a few 2G and 5G systems in the transition phase. Because of the dominant proportion and extensive data availability, we considered only 4G BTS networks in this study.
2. The proposed method does not consider telecom network elements other than those of BTS, including mobile switching, core transmission, data center, and retail office.
3. The locations of 4G BTS samples might not be sufficiently dispersed to represent all regions in Indonesia.
4. The variation in traffic volume & resulting changes in energy demand.

2.2.2 Framework Application

We adopted a method commonly used in the building sector to calculate the energy demand of a building stock. This was not only because a telecom site is comparable to a "building" but also because the building sector is more mature and advanced in research on energy system efficiency and emission reduction. Following the studies by Yamaguchi et al. [34] and Mata et al. [35], who created a framework for building stock aggregation, our proposed method involves four general steps, namely, segmentation, characterization, quantification, and aggregation.

Figure 2-2 shows the procedure for model development. In the segmentation step, the BTS samples were segmented based on parameters so that they could be grouped together according to their similar characteristics. In the characterization step, each BTS archetype representing a BTS segment was developed by characterizing the physical and technical elements of the BTS. The quantification step determines the daily power consumption of each BTS segment. Finally, the aggregation process estimates the proportion distribution for each BTS segment and calculates the stock-level power consumption of the telecom network by multiplying the power consumption per BTS for each archetype by the number of BTSs in the segment.

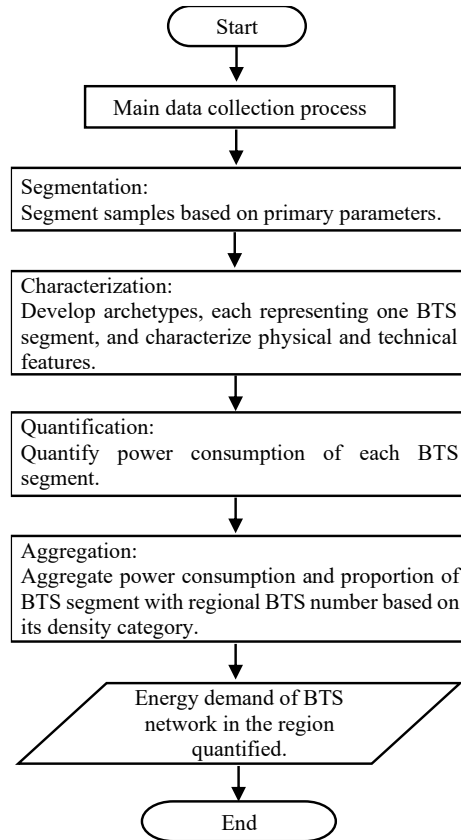


Figure 2-2. Foundational energy demand model for telecom network development workflow

(1) Segmentation

The samples from the telecom site profile database were segmented based on three main parameters: 1) density category, 2) BTS type, and 3) system configuration. The number of system configuration combinations will be numerous if we consider all radio details. As illustrated earlier, one BTS equipment can transmit three different signal layers simultaneously. Therefore, we simplified the segmentation by considering only if the system configuration i has one, two, or three systems for each BTS.

In addition, we added one BTS type to represent the hub sites that use shelter and indoor equipment based on an interview with an expert from one of the telecom equipment vendors. The expert mentioned that hub sites are used to interconnect an average of 10 macro sites. Shelters continue to be used because of the need to install additional equipment, including existing 2G BTSs. All sites with shelters require air conditioning to maintain the temperature of the equipment. Following these considerations, we randomly selected macro sites to add 2 kW of power to compensate for 2G BTSs, air conditioning, and other utility usage; we called this a “macro hub” site. In macro-level calculations, the focus is on total power consumption; hence, the specific location is not critical. Therefore, random selection is sufficient for this purpose as long as the associated criteria are met.

We considered a BTS segment k comprising 36 combinations. The segment name is derived by combining the BTS type and number of configurations contained in it (e.g., PIC_ i is a pico BTS with i -system configuration). Regarding the BTS type and system configuration, the physical and technical characteristics of BTSs are considerably different. However, the differences between the four density categories have not been clarified. Hence, we conducted statistical tests for each combination to evaluate whether the density category d , significantly alters the average peak power consumption. We applied Welch's, Mann–Whitney U, and t-test to combinations with two distinct density categories, whereas Kruskal–Wallis and Dunn's post-hoc test were applied to those with more than two categories. After eliminating non-significant combinations through statistical testing, the city- or district-level proportion table of each BTS segment k with specific density categories d was created. The proportion of BTS segment for each density category $S(k, d)$, was determined based on the distribution of these combinations in the site profile database. The statistical test reduced the BTS segment k to only 20 segments across density categories d .

(2) Characterization

A BTS archetype represents one BTS segment and is characterized by the physical and technical elements of the common BTS implementation characteristics in the region. The cabinet used for the BTS, antenna height, and deployment types are physical characteristics that differentiate BTS implementations in Indonesia and affect power consumption. The choice of the BTS cabinets influences the antenna distance and use of air conditioning. The height of the antenna affects the type or length of feeder used and determines the distance of signal coverage. Lastly, the deployment indicates the common places to deploy the BTS based on the BTS type and space availability. These details are useful considerations for an HRES.

Regarding the technical characteristics, because of data and access limitations, we did not obtain detailed BTS features such as sleep mode, adaptive modulation, or self-optimized antenna tilt. We used the historical BTS log file data from four different BTSs representing each density category. Based on the data, we characterized the operational characteristics of the BTS archetypes as changes in the power consumption with the power factor $x(t)$ ranging between 0 and 1 depending on the time-of-day t . The log file contains four-month hourly resolution data averaged on a 24-hour cycle. The highest power consumption in the cycle was determined as the peak power consumption P_{peak} . Thus, the changes in the power factor $x(t)$ relative to the peak consumption at the time of the day t can be determined. It is necessary to characterize the power consumption during the peak hour as 100% and the power factor change rate during the remaining day relative to the peak.

(3) Quantification

The power consumption of each BTS segment k at time t , $P(k, t)$, was calculated as shown in (2-1) by using the peak power consumption of each BTS segment and power factor $x(t)$ quantified in the time

series power consumption calculation model by following the time series pattern developed in the previous step.

$$P(k,t)=P_{\text{peak}}(k) \cdot x(t) \quad 2-1$$

Note that the hourly consumption profile was assumed to be generated daily for a year to calculate the annual power consumption of all BTS segments.

(4) Aggregation

The total daily power consumption of the BTS stock, P_{stock} , was quantified using (2-2), where $N_{\text{seg}}(\text{rgn},k)$ indicates the number of BTSs per segment k ($=1$ to K) for each region rgn ($=1$ to RGN) and $P(k,t)$ the power consumption of each BTS segment k at time t .

$$P_{\text{stock}} = \sum_{\text{rgn}=1}^{\text{RGN}} \sum_{k=1}^K \sum_{t=1}^{24} P(k,t) \cdot N_{\text{seg}}(\text{rgn},k) \quad 2-2$$

The first step to determine the number of BTSs in the region for each segment, $N_{\text{seg}}(\text{rgn},k)$, was to quantify the ratio r of BTS per thousand population by dividing the total 4G BTS network share of four telecom operators, which is 431,574 BTSs, and thousand scale of the population in Indonesia. The ratio r [unit/1000 people] was then multiplied by the thousand-scaled regional population to quantify the number of BTSs in the region $N(\text{rgn})$. The total number of BTS per region $N(\text{rgn})$ was then split by segment using the proportion of BTS segment for each density category $S(k,d)$. Because d is a function to categorize the regional density and can be calculated based on the regional population and area, we replace d in the equation with rgn to determine the number of BTS in the regions for each segment $N_{\text{seg}}(\text{rgn},k)$. The regional scale in this equation means the district. Therefore, we need to add up the consumption from each district because our goal is to calculate P_{stock} at the provincial level which consists of several districts.

2.3 Results and Analysis

2.3.1 Segmentation

Figure 2-3 shows the average peak power consumption of the BTS samples classified by (a) density category, (b) BTS type, and (c) system configuration. As shown in Figure 2-3(a), urban areas have the highest variability of sample data compared to other categories between 1–9 kW with an average of 4.3 kW. Meanwhile, outliers are abundant in dense urban areas, indicating that there are many cases of overloaded BTS power consumption. The median and average peak power consumption shows not much differ in all density categories. This result indicates that the change in density category does not affect the average BTS power consumption. However, the average peak power consumption varies significantly with the BTS type and system configuration.

In Figure 2-3(b), macro hub BTS has the highest average peak power consumption, which is 6.7 kW, and 75% of the sample ranged between 4–8 kW. IBS BTS has an average peak power

consumption of 2.5 kW, whereas those of pico and micro BTSs average between 2.1–2.4 kW and that of macro BTS is 4.1 kW. In Figure 2-3(c), the increase in the number of system configurations increases the average power consumption. The peak was 4.8 kW for three-system configurations, followed by 2.4 kW and 2.0 kW for two- and one-system configurations. The two-system configuration has the least sample variability, indicating a capacity upgrade process that mostly goes directly to the highest system.

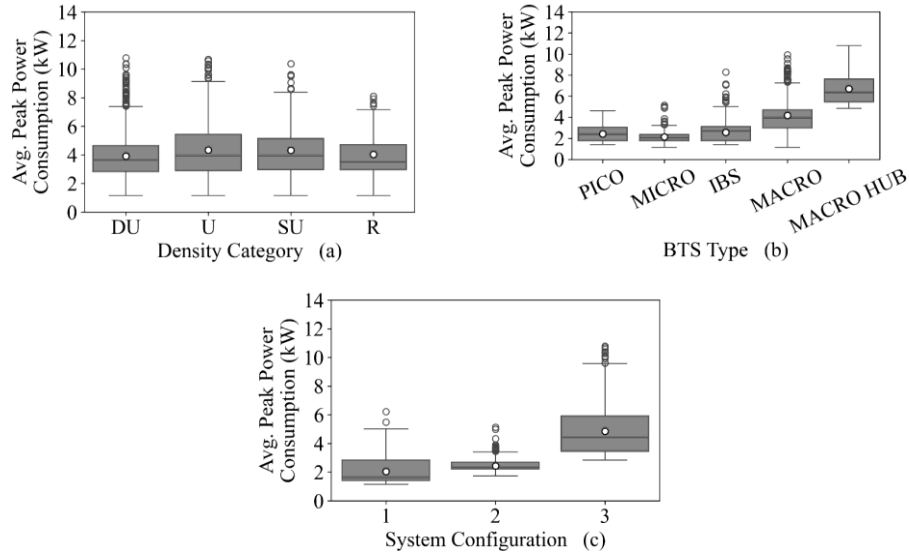


Figure 2-3. 4G BTS power consumption segmentation based on (a) density category, (b) system configuration, (c) BTS type

Figure 2-4 shows the quantified peak power consumption for BTS segments, evaluated by combining the system configuration and density category. As shown in the figure, the peak power consumption increased up to 5 kW for a 3- system-configuration BTS regardless of the density category. The line plot of BTSs with one-system configuration in dense urban areas shows the highest average peak power consumption of approximately 2.2 kW. However, when the configuration complexity increases, the average peak power consumption in rural, suburban, and urban areas exceed that in dense urban areas.

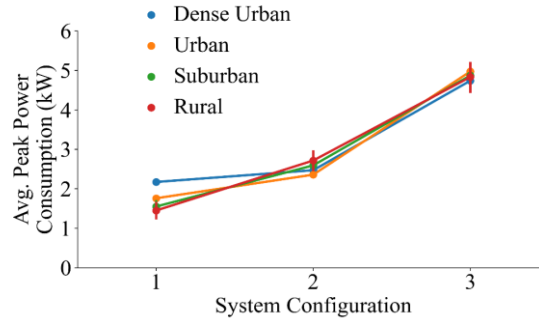


Figure 2-4. Plot line of BTS peak power consumption based on system configuration and density category.

Similar results were obtained even for various BTS types, as shown in Figure 2-5. Statistical differences based on the density category were evaluated for these results. Only PIC_3, IBS_1, and IBS_3 showed distinctive differences of approximately 0.4–0.6 kW in the average power consumption among the density categories. The average power consumptions of the other combinations were relatively similar, as observed in Figure 2-3(a). Appendix A lists 36 combinations used to analyze the distribution, including the average peak power consumption and proportion of each BTS in the samples.

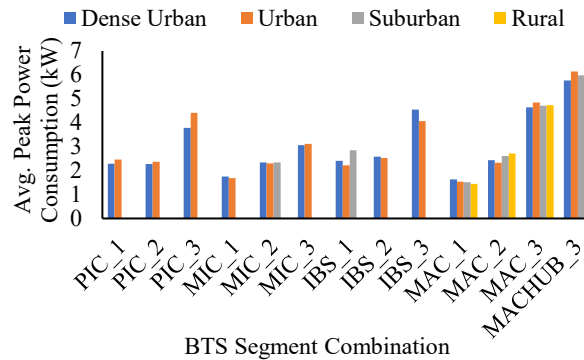


Figure 2-5. Peak power consumptions of 4G BTS segment combinations for different density categories.

Table 2-4 shows the significance of power consumption based on the statistical test results of the density category. Pico, micro, IBS, and macro hub BTS with all types of system configurations showed no significant difference in the average power consumption among the density categories, with a p-value greater than 0.05. On the contrary, regardless of the configuration, the density category had a significant effect on the power consumption for macro BTS.

Table 2-4. Statistical test results for power consumption

BTS type	Syst conf.	p-value based on density category
Pico	1	a= 0.505; b= 0.470; c= 0.505
	2	a= 0.744; b=0.901; c=0.744
	3	a= 1; b= 1; c= 1

Micro	1	a= 0.296; b= 0.497; c= 0.296
	2	d= 0.948
	3	a= 0.526; b= 0.307; c= 0.526
IBS	1	d= 0.432
	2	a= 0.599; b= 0.778 c= 0.599
	3	a= 0.178; b= 0.365; c= 0.178
Macro	1	d= 0.027
	2	d< 0.001
	3	d= 0.005
Macro Hub	3	d= 0.074

a= Welch's t-test; b= Mann–Whitney U test; c= unequal variance t-test; d= Kruskal–Wallis test

The significant Kruskal–Wallis results were followed up with Dunn’s post-hoc test to identify the specific density categories with significant differences. Dunn’s test showed that only macros with two-system configurations were significantly affected in all density categories, whereas other macros were affected only in the dense urban and urban categories. This result can be inferred from Table 2-2, which shows that the samples located in dense urban and urban areas account for more than 90% of the respective proportions of BTSs. Thus, even small differences in power consumption result in significant differences in the overall consumption. Appendix B provides the complete Dunn’s post-hoc test results.

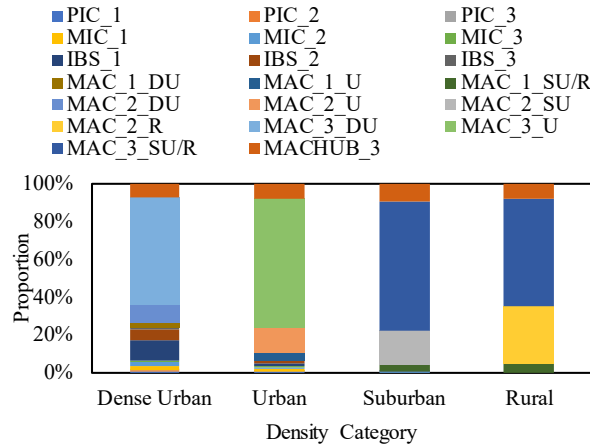


Figure 2-6. BTS segment proportion for each density category.

Figure 2-6 shows the proportion of 20 BTS segments based on the statistical test results for each density category, $S(k,d)$. Some BTS segments k are in all density categories d , but some others don’t, depending on the sample. City- or district-scale proportions were chosen over the national level to avoid unbalanced distribution when applying national-level proportions at the city or district level to calculate the energy demand. Instead, to calculate the energy demand at the national level, we can first decompose the scale into city or district levels to use the precise proportion table. The detailed proportion of the BTS segment is provided in Appendix B.

2.3.2 Characterization

Table 2-5 shows the characteristics of each BTS segment based on the statistical test results, along with the physical and technical characteristics, to develop a BTS archetype. For example, pico and micro BTSs are installed using an outdoor cabinet with up to 10 m of antenna height. They are commonly deployed at roadside poles, rooftops, or the main front exterior faces of the building (façades). This complies with the common purpose of pico and micro BTSs, which are used to cover blank spots and high-demand users in specific areas to avoid large signal coverage. The average peak power consumption is also shown in the table to represent the effect of the physical attributes of the archetypes.

Table 2-5. Physical characteristics of BTS site archetype

BTS segment	P_{peak} (kW)	BTS type	Used cabinet	Ant. height (m)	Deployment
PIC_1	2.3	Pico	Outdoor	3–5	Retail, Store Roadside Unit (RSU)
PIC_2	2.3				
PIC_3	4.0				
MIC_1	1.7	Micro	Outdoor	5–10	RSU, building façade, grid poles
MIC_2	2.3				
MIC_3	3.1				
IBS_1	2.4	IBS	Indoor	3–5	In-Building System
IBS_2	2.6				
IBS_3	4.4				
MAC_1_DU	1.6	Macro	Outdoor	15–30	Greenfield or Rooftop (outdoor)
MAC_1_U	1.5				
MAC_1_SU/R	1.5				
MAC_2_DU	2.4				
MAC_2_U	2.3				
MAC_2_SU	2.6				
MAC_2_R	2.7				
MAC_3_DU	4.4				
MAC_3_U	4.8				
MAC_3_SU/R	4.6				
MACHUB_3	6.7	Macro	Indoor	30–50	Greenfield (shelter) + Air Cond.

Figure 2-7 shows the daily data traffic and power consumption characteristics of the BTS for each density category. The power consumption patterns were analyzed based on the technical and operational characteristics. The data traffic served by the BTS affects its power consumption. The peak traffic capacity was observed at 8–9 pm, accompanied by high power consumption, whereas the lowest data traffic and power consumption occurred between 3–4 am. Although not identical, we can see from the graph that the power consumed (orange line) follows the data traffic (blue line) at all densities. It is noted that the BTS has a minimal power requirement, even in the idle state where traffic is very low or non-existent. Thus, the power consumption will never show a zero value.

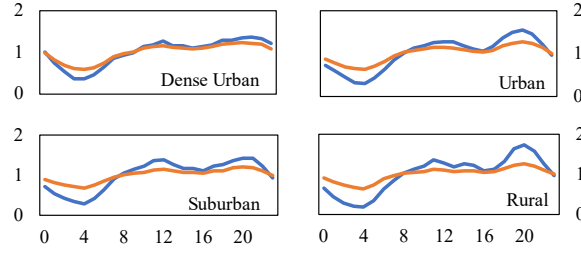


Figure 2-7. Daily 4G BTS traffic and power consumption characteristics for each density category.

We compared 24-hour cycle power consumption change rates relative to the peak among density categories and could not identify significant differences, as the results were less than 4%. Therefore, we applied the average of the power factors quantified for the four sample BTSs to all the BTS segments. Figure 2-8 shows the aggregated on-average relation between traffic and power consumption for four samples. The aggregated pattern does not change the peak and off-peak periods of the individual samples. Using Figure 2-8, the power factor x for hour (t) was identified as shown in Figure 2-9. The difference in power consumption between peak and off-peak hours was almost 50%, which began to rise up to 81% of the peak value at 8–9 am. After that, Power consumption decreased to 83% of the peak around 11 pm.

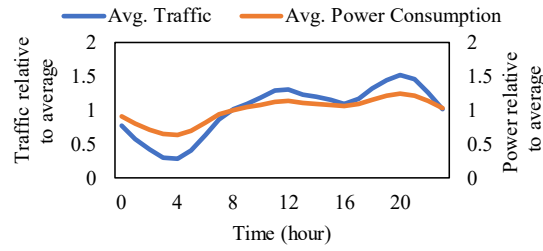


Figure 2-8. Characteristics of 4G BTS traffic and power consumption for all density categories.

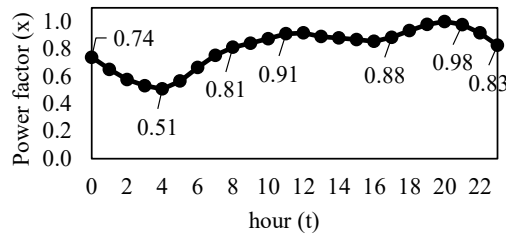


Figure 2-9. Time series 4G BTS power factor model.

2.3.3 Quantification

The power consumption at time t for each BTS segment k , $P(k,t)$ was calculated to compute (2-1) using the power factor $x(t)$ in Figure 2-9 and $P_{peak}(k)$ from Table 2-5. Figure 2-10 shows the annual energy demand for each BTS segment. MACHUB_3 consumes the most power annually (around 47 MWh/year), whereas MAC_1_SU/R consumes the least (11 MWh/year). It also shows that the BTS with three-system configurations consumes more power for each BTS type.

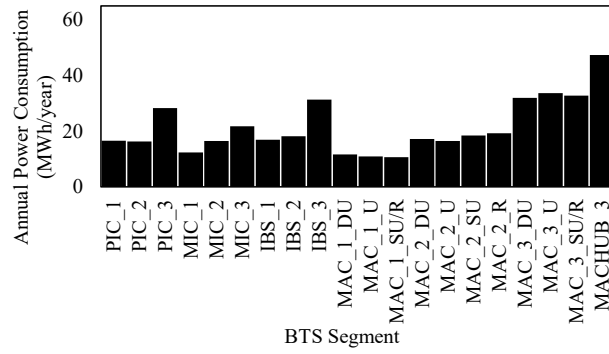


Figure 2-10. Comparison of annual power consumption of BTS segments.

2.3.4 Aggregation

The total population of 4.4 million people in Bali was divided into nine districts. Badung, Gianyar, and Denpasar districts were classified as urban, and the remaining districts were classified as suburban. With 1.56 as the ratio r of BTSs per thousand people, Bali is estimated to have 6,887 total BTSs in the region $N(rgn)$ —2,808 in the urban areas and 4,079 in the suburban areas. This number was equal to 1/63 compared to the BTS number that serves all of Indonesia. Buleleng district has 1,287 BTSs serving 825 thousand people, which is the highest among all districts. Denpasar is the second largest with 1,134 BTSs serving 727 thousand people. Klungkung district is the smallest with only 334 BTSs serving 214 thousand people. The detailed BTS count for each district can be found in Table 2-6. The count of BTS per segment for each region $Nseg(rgn, k)$ identified based on Figure 2-6 or Appendix C to calculate the aggregated power consumption.

Table 2-6. Number of BTSs per thousand population in Bali Province districts

District	Population (1,000)	People /km ²	Density category	r	N_{reg}
Jembrana	328	386	Suburban	1.56	512
Tabanan	469	553	Suburban	1.56	732
Klungkung	214	628	Suburban	1.56	334
Bangli	267	507	Suburban	1.56	417
Karangasem	511	609	Suburban	1.56	797
Buleleng	825	624	Suburban	1.56	1,287
Badung	550	1,378	Urban	1.56	857
Gianyar	524	1,438	Urban	1.56	817
Denpasar	727	5,774	Urban	1.56	1,134
Total					6,887

Figure 2-11 shows the aggregated total annual energy demand of BTS stocks, P_{stock} for each segment k in nine district regions rgn of Bali. Macro with three-system configuration dominates the proportions of the BTS segment in both urban and suburban areas, accounting for 70% of the proportions. Although categorized as suburban, Buleleng district has the highest annual demand of approximately 40 GWh/year because it serves the largest population and area. The districts of Denpasar, Badung, and Gianyar are categorized as urban areas and have the next highest annual

demand, with 35 GWh/year, 26 GWh/year, and 25 GWh/year, respectively. The total annual energy demand for the BTS network in Bali is approximately 211 GWh/year, of which 40% is for urban areas and the remaining 60% is for suburban areas. See Appendix D for details on the number of BTS segments and their power consumption in each district.

Figure 2-12 shows the hourly energy demand of BTS stocks P_{stock} for each district rgn in Bali for a 24-hour t cycle. The BTS networks in Buleleng district account for the highest hourly energy demand of 4.5 MW, whereas Klungkung district has the lowest average power of 1.2 MW. The total daily energy demand for the 4G BTS network in Bali is approximately 578 MWh/day or equal to 24 MW of daily average power rating. From the figure, we can see that the lowest energy demand of 15 MWh was at 4 am, and the peak energy demand of 30 MWh was at 8 pm.

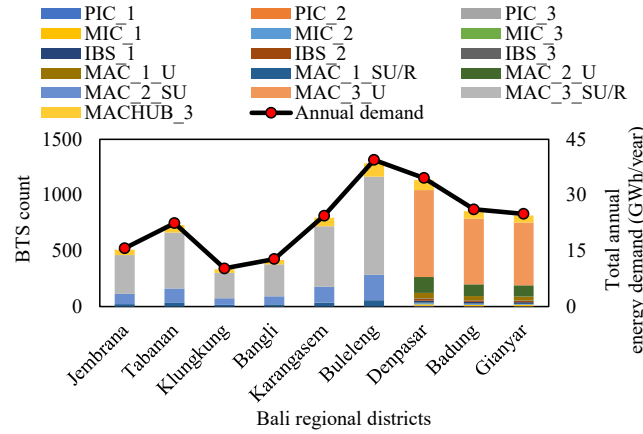


Figure 2-11. 4G BTS counts and annual energy demand in Bali districts.

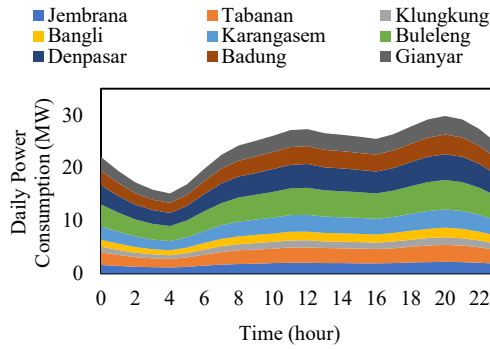


Figure 2-12. Total 4G BTS daily power consumption in Bali Province districts

2.4 Discussion

This research established four steps of the macro-level BTS stock energy demand model: segmentation, characterization, quantification, and aggregation. The results showed that the annual energy demand for the 4G BTS network in Bali province was 211 GWh/year, or 3.8% of the total electricity consumption in Bali of around 5,470 GWh/year, in 2022. We found that the type, system configuration, and proportion of the BTS strongly influence the energy demand calculation for the BTS network at

the macro level. The density category also affects the respective proportion of the BTS segments according to the population. With this model, we were also able to identify the peak and off-peak hours from the data traffic of mobile phone subscribers in Indonesia.

Each step of the model framework was evaluated and the uncertainty is discussed below to determine necessary improvements. In the segmentation step, Figure 2-3(a) shows that the BTS power consumption in rural and suburban areas is relatively high. This is because operators deploy BTSs less frequently in those regions and each BTS covers a wider area. The plot line in Figure 2-4 shows that telecommunication operators are seeking a balance between network coverage and quality of service. In addition, this result shows that the economic activities and financial status of the Indonesian population have increased significantly in the suburbs. Figure 2-6 shows that the proportion of macro BTSs is high among the BTS samples. This result indicates that Indonesia's telecom operators continue to prioritize coverage over high-speed connections. Indonesia is ranked 101 out of 144 countries, with an average mobile internet speed of 25.37 Mbps [36].

The proportion table for 20 BTS segments in Appendix B was created based on the combination of BTS type, system configuration, and statistical test result to determine the significance between density categories. It can be used to calculate the energy demand for another region after adjusting for the local population. However, uncertainty arises regarding whether the database sample is sufficient to represent the actual BTS network, as our samples are limited to Indonesia's two most developed and densely populated provinces in Java island. Of course, this can be addressed by analyzing the comparison after adding the number of BTSs in another island outside of Java and widening the distribution of the BTS samples to increase the accuracy of the proportion table.

Subsequently, physical and technical characteristics were added to determine the BTS archetypes and power factor of 4G BTS in a 24-hour cycle in the characterization step. In Figure 2-8, we observed the traffic demand of Indonesian mobile users. This characteristic is slightly different from the conditions in North America, Western Europe, and Japan, which are considered to have more mature users, as shown in Figure 2-13. Further analysis is needed to understand why the slope occurs only between 13:00 and 17:00 in our BTS traffic, whereas the traffic in the reference countries is more stable. Note that in this study, the daily cycle of BTS traffic and power consumption is based solely on the average of the data from four BTS log files. To ensure that the cycle in the proposed time series BTS power factor model is properly implemented across regions and time, it is necessary to add historical BTS log samples from different density areas and periods to improve representability. In the quantification step, we calculated the annual performance by assuming that the hourly consumption profile repeats every day for a year, without considering weekends or holidays. This aspect can be improved if additional load profile information becomes available.

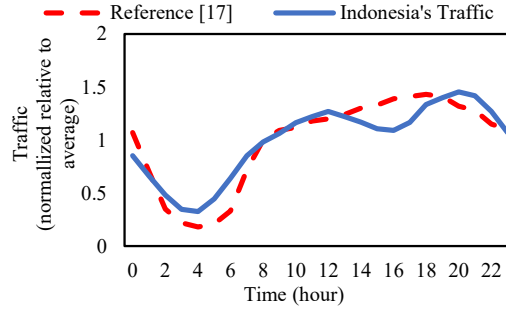


Figure 2-13. Comparison of 4G BTS traffic characteristics between Indonesia and developed countries.

The number of BTSs per thousand people plays a very important role in this study as a reference for calculating the energy demand in the aggregation step. Because no method in existing literature can provide an exact figure, the current BTS share in Indonesia and the population size are used to calculate the number of BTSs per thousand people. However, it is necessary to discuss whether the population considered is the entire population or only the population of mobile service users. The BTS per thousand people also needs to be adjusted to apply this method to other countries owing to its very specific nature.

Calculated on a national scale, by multiplying the BTS power consumption $P(k,t)$ with the number of BTSs per segment for each region, $N_{seg}(rgn,k)$, in every province in Indonesia, our model estimates that the annual energy demand for the 4G BTS network will be 12.7 TWh/year or 4.6% of the national electricity sales of approximately 274 TWh/year in 2022. This indicates that 4G BTS networks in Indonesia have 1.4 GW average power rating. To date, we have not found any reference to verify the results of our model, even from official government reports. Nevertheless, we could use the 4G BTS load data reported by other researchers and multiply the data by the 4G BTS number in Indonesia. Rizqiawan et al. [31] stated that the average BTS power consumption from eight samples based on an actual survey was 5.6 kW. Vereecken et al. [37] stated that the 4G BTS power consumption was around 3.7 kW per base station, whereas Etoh et al. [16] used 5 kW per BTS to calculate the total power consumption.

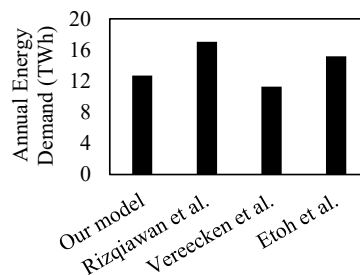


Figure 2-14. Comparison of 4G BTS annual energy demand in Indonesia.

We used these values to calculate the annual energy demand for the entire 4G BTSs in Indonesia, as shown in Figure 2-14. The results show that the BTS network consumes 11, 15, and 17 TWh

annually or 4.1%, 5.5%, and 6.2% of the national electricity consumption, respectively. We are convinced regarding the reliability of our model because the result of 4.6% was consistent with that in comparable studies. Of course, this comparison is not ideal, as the power consumption of the entire network cannot be calculated from the data of just one sample. However, the result shows that our research is proceeding in the right direction.

Figure 2-15 compares the electricity consumption of telecommunications networks in Indonesia, Japan, and European countries as percentages of the total national electricity consumption. We used the reports from the Japan Science and Technology Agency (JST) [38] in 2020 and the European Commission [39] in 2024 for comparison with our results. The telecommunication networks in Japan consume more than 12 TWh of energy, accounting for 1.3% of the national consumption. The telecommunication networks in Germany and Spain account for 1.4% of their national consumption, whereas those in Italy account for 1.3%. The telecommunication networks in smaller European countries such as Cyprus, Latvia, Estonia, and Lithuania exhibit a share of more than 2%, similar to the data for Indonesia. Indonesia's low per capita electricity consumption, which is only 1.2 MWh/person/year, will affect the total national electricity consumption, resulting in a high overall share. Although other countries considered in the comparison have electricity consumption exceeding 5 MWh/person/year, the proportion consumed by telecom networks will be lower.

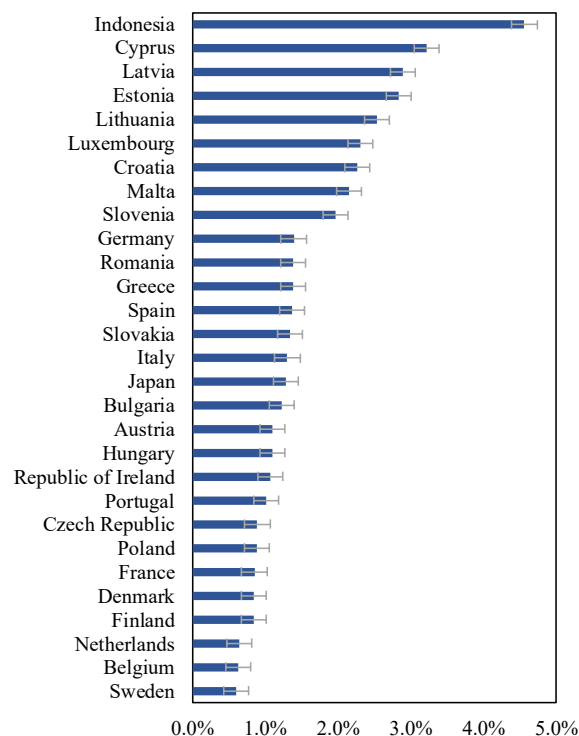


Figure 2-15. Electricity usage share of telecom network of the national consumption in various countries.

Our model has addressed the issue of calculating the energy demand of telecom networks at the macro level. The method can be implemented with only a small adjustment to the density category of the region being calculated. However, it has the limitation that it excludes 5G BTS from the calculation. Therefore, it may not be applicable to countries that have already transitioned to 5G. Lastly, our future research direction is to minimize the cause of uncertainty and enhance this research by calculating the energy supply potential of renewable power plants based on the obtained energy demand data for Bali.

2.5 Conclusion

This study demonstrated macro-level energy demand calculations based on density category information and representative BTS segments. The proposed method can be used to predict the energy demand of a BTS network for an entire region, not just for individual sites. The method can also be applied to other regions after making adjustments to the local condition. The segmentation and characterization to create an archetype and proportion table can be extended to HRES implementation for BTS networks. We calculated that the 4G BTS network in the Bali region accounts for 3.8% of the total electricity sales in Bali and 4.6% of Indonesia's national electricity consumption. These numbers indicate that HRES is needed by telecom operators as a strategy to achieve efficiency. It also indicates how the telecommunication sector plays an important role in achieving the carbon neutrality target set by the government in 2060. Lastly, the large share of the total electricity consumption indicates that the potential for HRES implementation in BTS networks will be high in the future.

2.6 Appendix

2.6.1 Appendix A. Distribution of density category, system configuration and BTS type

Site Type	1 System		2 System		3 system		Avg. Peak Power Consumption (kW)	Proportion
	Avg. Peak Power Consumption (kW)	Proportion	Avg. Peak Power Consumption (kW)	Proportion	Avg. Peak Power Consumption (kW)	Proportion		
Dense Urban	2.17	8.49%	2.47	8.71%	4.74	33.09%	3.91	50.30%
IBS	2.41	5.46%	2.58	2.84%	4.54	0.42%	2.57	8.73%
MACRO	1.64	1.45%	2.43	4.60%	4.53	28.60%	4.13	34.65%
MACRO HUB	0.00	0.00%		0.00%	6.56	3.72%	6.56	3.72%
MICRO	1.76	1.36%	2.34	1.07%	3.06	0.33%	2.14	2.76%
PICO	2.29	0.21%	2.27	0.21%	3.79	0.02%	2.36	0.45%
Urban	1.75	3.10%	2.35	6.30%	4.97	32.20%	4.34	41.60%
IBS	2.22	0.70%	2.53	0.65%	4.06	0.13%	2.52	1.48%
MACRO	1.54	1.79%	2.33	5.16%	4.76	28.64%	4.25	35.59%
MACRO HUB	0.00	0.00%	0.00	0.00%	6.92	3.30%	6.92	3.30%
MICRO	1.69	0.49%	2.30	0.40%	3.12	0.13%	2.11	1.02%
PICO	2.46	0.11%	2.37	0.09%	4.41	0.01%	2.53	0.21%
Suburban	1.57	0.28%	2.61	1.22%	4.86	5.29%	4.32	6.79%
IBS	2.85	0.01%	0.00	0.00%	0.00	0.00%	2.85	0.01%
MACRO	1.51	0.27%	2.61	1.21%	4.46	4.64%	4.10	6.12%
MACRO HUB	0.00	0.00%	0.00	0.00%	6.41	0.65%	6.41	0.65%
MICRO	0.00	0.00%	2.34	0.01%	0.00	0.00%	2.34	0.01%
Rural	1.44	0.06%	2.71	0.40%	4.83	0.86%	4.04	1.31%
MACRO	1.44	0.06%	2.71	0.40%	4.63	0.77%	3.84	1.23%
MACRO HUB	0.00	0.00%	0.00	0.00%	6.30	0.08%	6.30	0.08%
Grand Total	2.04	11.93%	2.44	16.63%	4.85	71.44%	4.12	100.00%

2.6.2 Appendix B. Dunn's Post-Hoc test results

MAC 1

Test	H-statistic	P-value	Significance	
Kruskal–Wallis	9.167	0.027	Significant	
Dunn	DU	U	SU	R
DU	1	0.056	0.359	0.520
U	0.056	1	1	1
SU	0.359	1	1	1
R	0.520	1	1	1

MAC 3

Test	H-statistic	P-value	Significance	
Kruskal–Wallis	13.006	0.005	Significant	
Dunn	DU	U	SU	R
DU	1	0.002	0.875	1
U	0.002	1	1	1
SU	0.875	1	1	1
R	1	1	1	1

MAC 2

Test	H-statistic	P-value	Significance	
Kruskal–Wallis	32.631	0.000	Significant	
Dunn	DU	U	SU	R
DU	1	>0.000	0.279	0.218
U	>0.000	1	>0.000	0.003
SU	0.279	>0.000	1	0.427
R	0.218	0.003	0.427	1

MACHUB 3

Test	H-statistic	P-value	Significance	
Kruskal–Wallis	6.927	0.074	Not Significant	
Dunn	DU	U	SU	R
DU	1	0.304	0.839	1
U	0.304	1	0.134	1
SU	0.839	0.134	1	1
R	1	1	1	1

Notes:

DU (Dense Urban); U (Urban); SU (Suburban); R (Rural)

2.6.3 Appendix C. Proportion of each BTS segment

BTS Segment k	P_{peak} (kW)	Proportion $S(k,d)$			
		Dense Urban	Urban	Sub Urban	Rural
PIC_1	2.34	0.42%	0.25%	-	-
PIC_2	2.30	0.42%	0.23%	-	-
PIC_3	4.00	0.05%	0.03%	-	-
MIC_1	1.74	2.70%	1.18%	-	-
MIC_2	2.33	2.12%	0.96%	0.17%	-
MIC_3	3.08	0.65%	0.31%	-	-
IBS_1	2.39	10.87%	1.70%	0.17%	-
IBS_2	2.57	5.64%	1.55%	-	-
IBS_3	4.43	0.84%	0.31%	-	-
MAC_1_DU	1.64	2.89%	-	-	-
MAC_1_U	1.54	-	4.31%	-	-
MAC_1_SU/R	1.50	-	-	3.97%	4.46%
MAC_2_DU	2.43	9.14%	-	-	-
MAC_2_U	2.33	-	12.40%	-	-
MAC_2_SU	2.61	-	-	17.79%	-
MAC_2_R	2.72	-	-	-	30.36%
MAC_3_DU	4.52	56.87%	-	-	-
MAC_3_U	4.76	-	68.85%	-	-
MAC_3_SU/R	4.64	-	-	68.40%	57.15%
MACHUB_3	6.70	7.39%	7.92%	9.50%	8.04%
		100%	100%	100%	100%

2.6.4 Appendix D. Bali province districts: Proportion of BTS and power consumption of each segment

Segment	Avg. peak consumption (kW)	Jembrana		Tabanan		Klungkung		Bangli		Karangasem		Buleleng		Denpasar		Badung		Gianyar	
		BTS count	Power cons. (kW)	BTS count	Power cons. (kW)	BTS count	Power cons. (kW)	BTS count	Power cons. (kW)	BTS count	Power cons. (kW)	BTS count	Power cons. (kW)	BTS count	Power cons. (kW)	BTS count	Power cons. (kW)	BTS count	Power cons. (kW)
PIC 1	2.34	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	3	6.6	2	5.0	2	4.8
PIC 2	2.30	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	3	6.0	2	4.5	2	4.3
PIC 3	4.00	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	0	1.4	0	1.0	0	1.0
MIC 1	1.74	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	13	23.3	10	17.6	10	16.8
MIC 2	2.33	1	2.0	1	2.9	1	1.3	1	1.7	1	3.2	2	5.1	11	25.4	8	19.2	8	18.3
MIC 3	3.08	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	4	10.8	3	8.2	3	7.8
IBS 1	2.39	1	2.1	1	3.0	1	1.4	1	1.7	1	3.2	2	5.2	19	46.0	15	34.8	14	33.2
IBS 2	2.57	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	18	45.2	13	34.2	13	32.6
IBS 3	4.43	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	3	15.6	3	11.8	2	11.2
MAC 1 U	1.54	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	49	75.3	37	56.9	35	54.2
MAC 1 SU/R	1.50	20	30.5	29	43.6	13	19.9	16	24.8	32	47.5	51	76.6	0	0.0	0	0.0	0	0.0
MAC 2 U	2.33	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	140	327.6	106	247.7	101	236.2
MAC 2 SU	2.61	91	237.5	130	340.0	59	155.0	74	193.5	142	370.3	229	597.7	0	0.0	0	0.0	0	0.0
MAC 3 U	4.76	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	-	0.0	781	3715.7	590	2809.3	562	2678.7
MAC 3 SU/R	4.64	350	1623.2	501	2323.7	228	1059.6	285	1322.6	545	2531.4	881	4085.3	0	0.0	0	0.0	0	0.0
MACHUB 3	6.70	48	325.5	70	466.0	32	212.5	40	265.2	76	507.7	122	819.3	90	601.8	68	455.0	65	433.9
TOTAL		511	2220.8	732.0	3179.2	334.0	1449.7	417.0	1809.5	797.0	3463.2	1287.0	5589.3	1134	4900.7	857	3705.2	817	3532.9

3 Enhancement of Macro-Level Energy Demand Model for Cellular Telecommunication Networks

3.1 Purpose

During the initial research stage, we developed a four-step macro-level model for estimating BTS stock energy demand using coarse-grained bottom-up data. However, refinement was needed to avoid overestimating the model's applicability across regions due to limited nationwide sample representation. To address this, we refined the model by integrating socio-economic factors to better estimate the BTS site stock for specific regions. Additionally, we increased the model's granularity by incorporating insights from stakeholder interviews, conducting comprehensive site surveys, and gathering newly collected data.

This second research stage aimed to address the absence of an energy demand modeling framework for cellular networks that takes into account the composition of BTS sites, their spatial distribution, along with the physical and technical characteristics that influence energy demand. We developed a modeling framework that concurrently represents the stock composition and BTS site details. The proposed framework was validated through a case study examining the entire stock of BTS sites in Indonesia. While the framework can accommodate HRES, their integration is not covered in this stage. The designed framework can be applied to other regions, including those with limited available data, by adjusting the processes according to the available data.

3.2 Methodology

3.2.1 Proposed Framework

Figure 3-1 shows the proposed framework called macro-level energy demand model for cellular telecommunication Networks (MED-CTN). This framework was developed as an extension of the method developed by Dinata et al. [40]. As illustrated in Section (iv) of Figure 3-1, the hourly energy demand of the BTS site stock, $Pstock_t$, was calculated as the product of the hourly power consumption per BTS site, PC_t , and the total number of BTS sites, NS , as shown in (3-1):

$$Pstock_t = \sum_{m=1}^M \sum_{y=1}^Y PC_{y,t} \times NS_{y,m} \quad 3-1$$

The model accounted for the variation in PC_t for site type y and NS among target regions m . This study focused on five major site types y — $y1$ = Pico, $y2$ = Micro, $y3$ = IBS, $y4$ = Macro, and $y5$ = Macro Hub—and denoted municipalities as region m according to the spatial resolution of the available data¹.

¹ Site types and their coverage include Pico (up to 250 m), Micro (up to 2 km), and Macro (up to 30 km). The in-building system (IBS) ensures connectivity inside buildings such as hotels, malls, apartments, and offices. A Macro hub typically interconnects around 10 sites.

The framework is developed based on BTS site sample data as illustrated in Figure 3-1(i). Each sample contains a site profile, including peak power consumption, used to develop BTS site type archetypes as in Figure 3-1(iii). In addition, combined with socioeconomic factors of municipalities, the sample data is used to model BTS site stock composition for each municipality as in Figure 3-1(ii).

$PC_{y,t}$ in (3-1) is quantified by developing BTS site archetypes, denoted as *archetype*, with which hourly energy was calculated considering the physical and technical characteristics of BTS sites developed using the sample dataset (see Figure 3-1(iii)). The modeling method of $PC_{y,t}$ could be adjusted according to data availability. Furthermore, $PC_{y,t}$ was quantified as $PC_{y,t} = Ppeak_y \times PF_{y,t}$, where $Ppeak_y$ denotes the peak power consumption for site type y and $PF_{y,t}$ represents the hourly power factor accounting for temporal variation in power consumption.

The most straightforward way to quantify NS is to use the number of BTS sites per capita or land area. However, we found a variation in the BTS site composition for each site type among municipalities. Therefore, $NS_{y,m}$, was quantified by (3-2) using the total number of BTS sites $sitecount_m$ and the proportion of site types $TP_{y,m}$ in the municipalities.

$$NS_{y,m} = sitecount_m \times TP_{y,m} \quad 3-2$$

$sitecount_m$ was derived from data provided by the Indonesian Ministry of Communication and Digital Affairs and representatives of telecom operators. However, it could be modeled using widely available socioeconomic factors. As illustrated in Figure 3-1(ii), $TP_{y,m}$ was quantified by applying a statistical model developed using the BTS site sample dataset, considering the socioeconomic factor V_m as the predictor as in (3-3). $TP_{y,m}$ could be estimated by selecting widely available variables such as V_m , even for regions with insufficient data.

$$TP_{y,m} = \sum_{i=1}^5 TP(y_i | V_m) \quad 3-3$$

The total energy demand was quantified using (3-1) fulfilled the first requirement. The development of a model of $NS_{y,m}$ comprising $sitecount_m$ and $TP_{y,m}$ enabled a representation of the stock composition of BTS sites, including the composition by site type and spatial distribution, fulfilling the second requirement. The third requirement was fulfilled by developing BTS site archetypes representing physical and technical features. Although we developed the framework for Indonesia, it could be extended to other regions with different data availabilities, as discussed in Section 3.4.

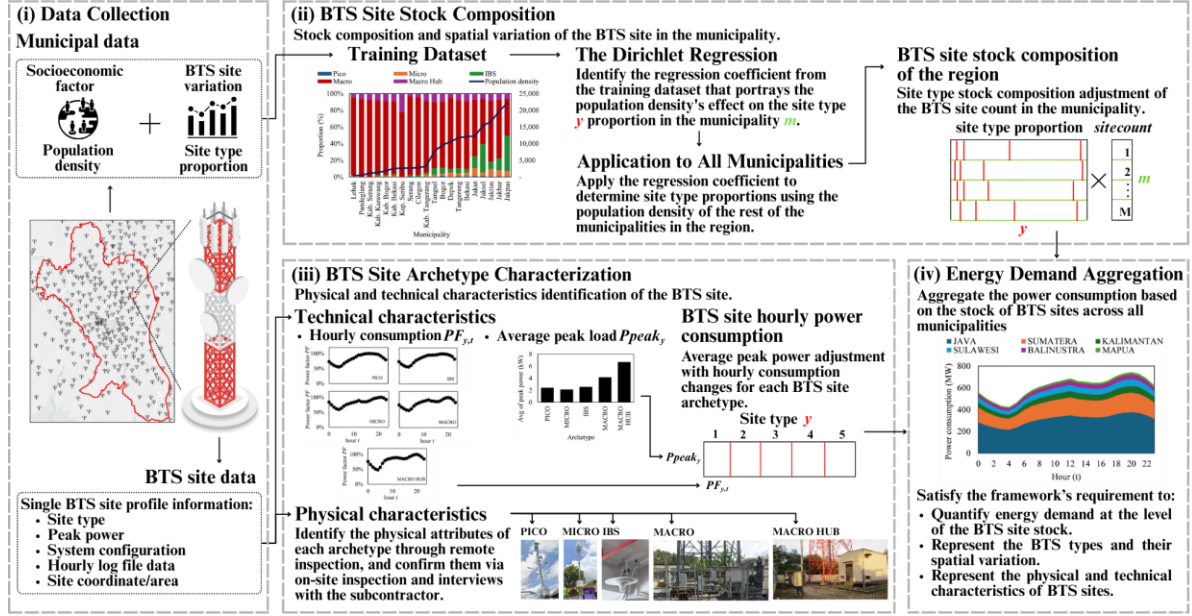


Figure 3-1. Overview of the proposed MED-CTN framework.

3.2.2 Case Study Context

3.2.2.1 Indonesian Cellular Network

Figure 3-2 shows a hexagonal model for BTS sites' area coverage using geometry [41]. This honeycomb-like design ensured complete signal coverage of the BTS sites, where R represents the cell radius. The implementation of cellular telecommunication networks in Indonesia is a combination of different technologies, from 2G to 5G, with various coverage radii as needed.

Although 2G BTS is important for legacy services, its total energy consumption is limited in total, and 3G BTS is being phased out. With the gradual rollout of 5G networks, 4G BTS currently serves as the dominant technology for high-speed cellular connectivity services. The number of 4G BTSs in Indonesia has been rapidly increasing; it was 327,827 in 2021 and 527,923 in 2023 [35, 36, 37, 38]. In fact, the annual growth rate is projected to be ~20% till 2029 [3].

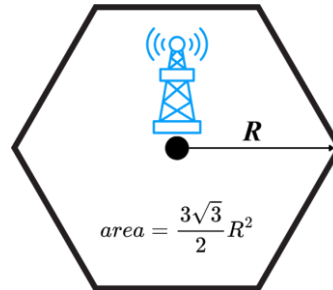


Figure 3-2. Cell coverage of BTS sites.

4G BTS network development corresponds to municipalities' socioeconomic development. According of a study [32], Indonesian municipalities can be classified into dense urban, urban,

suburban, and rural using the population size thresholds of 10,000, 1,000, and 300 people/km². The proportions for these 514 municipalities are 2%, 20%, 17%, and 61%, respectively.

3.2.2.2 Data

Table 3-1 lists the data used in this study. The BTS site sample dataset contains BTS site profiles, encompassing data from 8,527 sites distributed across 314 districts, 20 municipalities, and three provinces in Indonesia from high-density urban regions to rural areas. Figure 3-3 displays the proportion of the five BTS site types in the dataset. This dataset contains site-level information such as coordinates, network element (NE) configurations, site type, and peak power consumption [40].

The BTS power consumption log, *btslog*, is the hourly power consumption data recorded over three to four months at 4G BTS sites. Herein, we used *btslog* collected from 40 BTS sites, whereas only four samples were used in a previous study [40]. Samples were selected from the abovementioned dataset, considering site types, location density categories, and NE configurations. As explained in the previous section, the observed characteristics in the sample dataset were extended to the entire Indonesian population using the publicly available socioeconomic profiles listed in Table 3-1. The 4G cellular BTS number is explained in the following section.

Table 3-1. Primary data list

No.	Data collected	Details
1	BTS site sample dataset	The site profile includes coordinates, NE configurations, site type, and peak power consumption.
2	BTS power consumption log	Historical 4G BTS hourly power consumption data.
3	The socioeconomic profile of the municipality	The population density, human development index, and Indonesian digital society index were obtained from Indonesia's statistical bureau [27].
4	Number of municipal 4G cellular BTS	Municipal level data of cellular 4G BTS deployment by telecom operators.

■ PICO ■ MICRO ■ IBS ■ MACRO ■ MACRO HUB

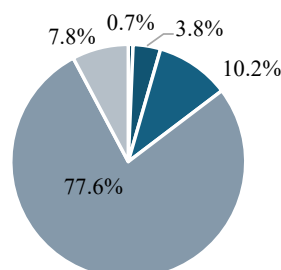


Figure 3-3. BTS site type segment and proportion of the samples.

3.2.2.3 BTS Site Count of Municipalities

In Indonesia, the number of BTS NEs is widely available, as major telecom operators disclose this information. We obtained the municipality-level number of 4G BTS NEs, bts_m , for 2022 through research visits to the Ministry of Communication and Digital Affairs in 2024. However, the energy consumption by these elements is unavailable because the energy consumption measurement is conducted at the BTS site level and a BTS site may integrate multiple NEs. For instance, telecom operators could install four 4G BTS NEs at one BTS site location, differentiated by the frequencies associated with their licenses. Therefore, the proposed framework used BTS sites as the modeling unit, instead of BTS NEs. The municipality-level number of BTS NEs was converted into the number of BTS sites, $sitecount_m$, as follows:

$$sitecount_m = \sum_{c=1}^4 \frac{prop_c}{NE_c} \times bts_m = 0.38 \times bts_m \quad 3-4$$

This equation uses the proportion of the number of NEs per BTS site listed in Table 3-2 ranging from 1 to 4. The proportion was derived from the BTS site sample dataset and verified through interviews with representatives of a telecommunications operator in Indonesia.

Table 3-2 . Indonesia's NE proportion of 4G RAN

BTS site configuration (<i>c</i>)	Network elements (<i>NEs</i>)	BTS site proportion (<i>prop</i>)
1	1	8%
2	2	18%
3	3	31%
4	4	43%

3.2.3 Application of MED-CTN Model

3.2.3.1 BTS Site Stock Modeling

For $TP(y_i|V_m)$ in (3-3), the Dirichlet distribution regression model [40, 41] was developed using the sample dataset with 20 municipalities in the three provinces. We considered population density, human development index, and Indonesia digital society index available for these municipalities, denoted as V_m , which was applied to the regression model to quantify $TP_{y,m}$. All values in the Dirichlet regression training dataset were normalized. Figure 3-4 shows the Dirichlet regression training dataset along with the population density. Through statistical modeling of $TP_{y,m}$, the observed characteristics of the sample dataset could be extended to other regions with necessary adjustments based on regional conditions.

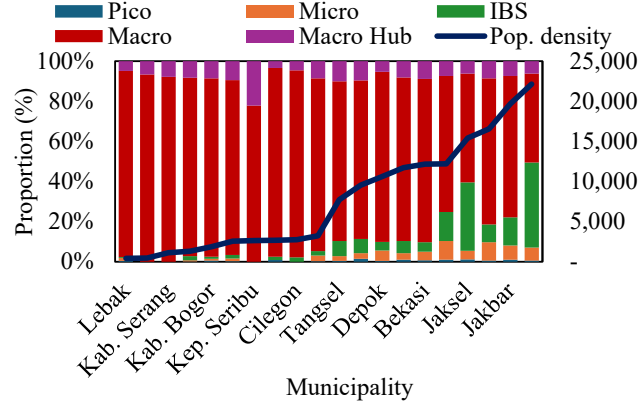


Figure 3-4. Dirichlet regression training dataset.

3.2.3.2 BTS Site Archetype Characterization

Herein, the method used for archetype development represents an advancement over previous approaches reported in the literature [40]. It encompassed detailed physical (*physic*) and technical characteristics, represented by the average peak power consumption P_{peak} and hourly power factor PF_t , of each BTS site type y as follows:

$$\text{archetype} = \{\text{physic}_y, P_{peak}_y, PF_{y,t}\} \quad 3-5$$

b. Physical characteristics (*physic_y*)

We considered the physical features that distinguished the types of BTS sites. These features were obtained from the BTS site sample dataset and technical documents from vendors. The physical appearance and average site area of these archetypes were also analyzed. The remote inspections used Google Maps' street view and aerial imagery for the site location coordinates obtained from the sample dataset. For the verification process, on-site inspections were performed by visiting two telecom sites and interviewing the corresponding application service provider subcontractors.

c. Technical characteristics

P_{peak}_y was calculated using the average power consumption of the BTS site samples for each site type y . $PF_{y,t}$ for each site type (3-6) was calculated as the average hourly profile divided by the peak consumption of the average, where $btslog$ was calculated using (3-7).

$$PF_{y,t} = \frac{\overline{x_{y,t}}}{\max(\overline{x_{y,t}})} \quad 3-6$$

$$\overline{x_{y,t}} = \frac{1}{btslog_{y,t}} \sum_{i=1}^{btslog_{y,t}} x_{y,t,i} \quad 3-7$$

3.3 Result and Analysis

3.3.1 Modeling of BTS site Stock

3.3.1.1 Dirichlet Regression Model

The regression coefficients listed in Table 3-3 were obtained by applying the Dirichlet regression model to the training dataset. Only the population density was selected as a significant factor.

Table 3-3. Optimized Dirichlet regression model coefficients

Site type y	Intercept	Coefficient
PICO	-1.05	0.41
MICRO	-0.63	0.86
IBS	-0.12	1.13
MACRO	2.72	-0.02
MACRO HUB	0.58	0.08

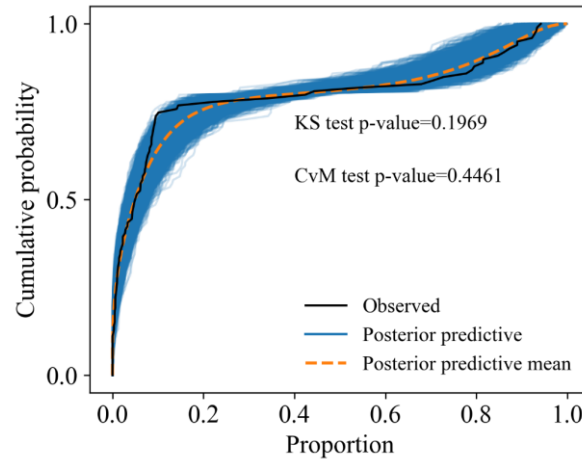


Figure 3-5. Cumulative density function for posterior predictive check.

Figure 3-5 shows the observed and predicted results of the cumulative distribution function (CDF) for the training data used for evaluating the model performance. The predicted CDFs, shown as blue lines, closely matched the observed CDF (solid black line), as the latter remained within the light blue confidence bands. A combination of lines was used to shape the blue band, with each line representing the posterior distribution of the Dirichlet regression model simulation. The model passed the Kolmogorov–Smirnov and Cramér–von Mises tests with p -values of 0.12 and 0.45, respectively.

3.3.1.2 Application to Indonesia Municipalities

Figure 3-6 presents the estimated site proportion $TP_{y,m}$, as defined in 3-3, for municipalities in Indonesia, plotted against population density on the horizontal axis. The most substantial changes were observed in the IBS and Macro site proportions because an increase in population density increased the proportion of IBS while decreasing that of Macro sites. Changes in site type proportion began when the population density exceeded 5,000 people/km², and the predominant site type switched to IBS when it exceeded 25,000 people/km². The IBS deployment continually increased in terms of number, while there have been no significant additions to Macro sites, as the basic cellular coverage.

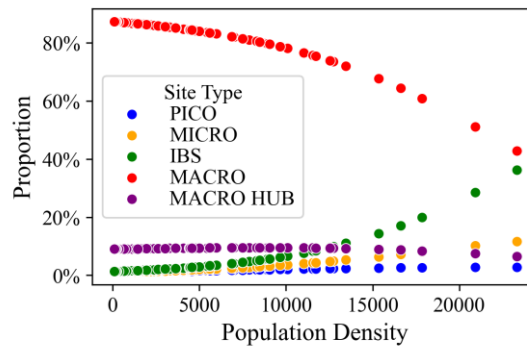


Figure 3-6. BTS site type proportion for 514 Indonesia municipalities $TP_{y,m}$.

3.3.2 BTS Site Archetype Characterization

3.3.2.1 Physical Characteristics (*physic_y*)

Figure 3-7 presents two remote inspection samples from 300 sites representing various site types and population density categories to identify the typical physical characteristics of BTSs. Appendix A summarizes the archetype features, including BTS equipment cabinet types, antenna elevations, deployment, average site area, and physical appearance.

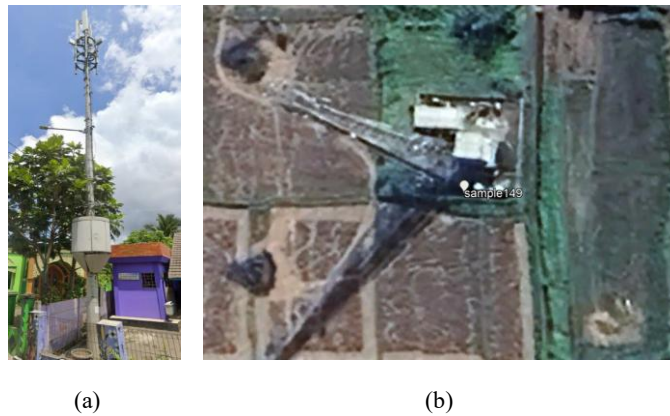


Figure 3-7. Remote site inspection: (a) street view and (b) aerial view.

3.3.2.2 Technical Characteristics

a. Average peak power consumption ($P_{peak,y}$)

Figure 3-8 shows the average peak power consumption for each BTS site type $P_{peak,y}$. Macro Hub had an average electricity consumption of 6.7 kW, which was higher than that of the other types because of the larger amount of installed equipment and the number of air conditioning units. A Macro site required a substantial amount of power, averaging 4.2 kW, because of the increased traffic from its extended coverage. Although the Pico sites had limited coverage, they were often located in areas with high population density and significant traffic potential. Therefore, the peak power consumption of these sites was higher than that of the Micro sites, with averages of 2.4 and 2.1 kW, respectively. The IBS sites exhibited an average power consumption of 2.6 kW.

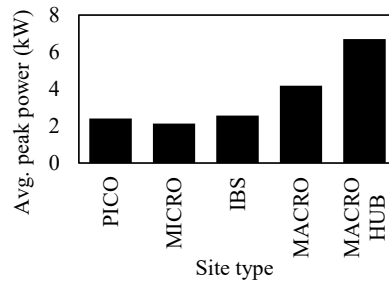


Figure 3-8. Average peak power consumption $P_{peak,y}$ according to the BTS site type

b. Hourly power factor ratio ($PF_{y,t}$)

Figure 3-9 shows $PF_{y,t}$. The power consumption during peak hours was twice that of the lowest hour depending on the traffic volume. Each site type exhibited a distinct hourly consumption pattern; however, all sites shared the same lowest consumption hour, which was 4 a.m. The peaks indicated high activity levels across residential, commercial, and industrial sectors, where industrial loads dominated daytime consumption and residential usage drove the evening peaks.

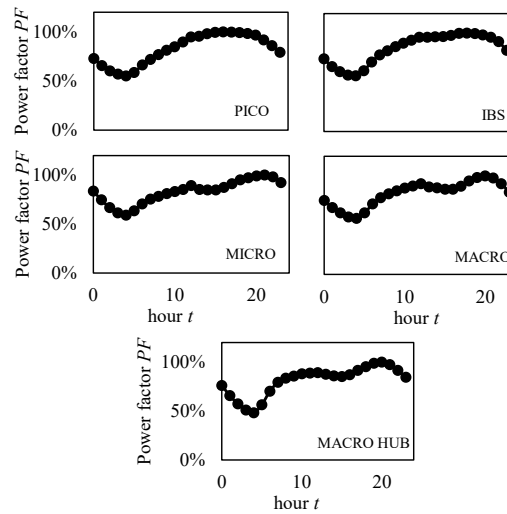


Figure 3-9. Hourly power factor ratio ($PF_{y,t}$) for each type of BTS site.

3.3.3 Energy Demand Quantification

3.3.3.1 Hourly Power Consumption ($PC_{y,t}$)

Figure 3-10 shows the hourly power consumption, with peak consumption corresponding to those in Figure 3-8 and hourly patterns consistent with those shown in Figure 3-9. Macro Hub exhibited the highest energy consumption, averaging ~ 130 kWh/day or 5.4 kW. This high usage was attributed to its design, which connected at least 10 BTS sites in a cellular network. Therefore, the transmission equipment installed in the Macro Hub was considerably more extensive than that found in standard sites.

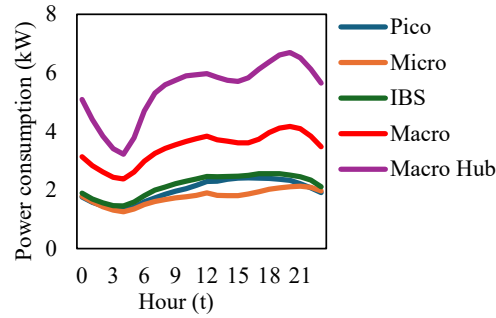


Figure 3-10. Hourly power consumption ($PC_{y,t}$) for each BTS site type.

3.3.3.2 Total Number of BTS Site ($NS_{y,m}$)

The $sitecount_m$ result from (3-4) was used to extend the analysis by calculating the average BTS site density and cell radius in each municipality (Figure 3-11). Municipalities are represented by their population density [48], and values in all axes were converted to $\log_{10}$ for better visualization. The density of the BTS site was obtained by dividing the total number of BTS sites by land size (km^2). This method calculates the average number of BTS sites deployed per square kilometer of the region, which is equivalent to determining a single BTS site's average hexagonal coverage area. To determine the cell radius for each BTS site, we inverted the hexagonal geometry formula shown in Figure 3-2 to calculate the cell radius R as the area was already identified. The figure illustrates the correlation between BTS site cell radius and population density, showing that BTS sites exhibit smaller coverage radii in densely populated areas than those in rural regions. Conversely, the density of BTS sites increased with increasing population density.

Furthermore, we identified the density of BTS sites per population by dividing $sitecount_m$ by a thousand people of each municipality population [48] (Figure 3-12). This yielded an average density of 0.64 BTS sites for every 1,000 people, equal to a single BTS site serving $\sim 1,560$ people. No statistically significant changes were found based on the population density as the p -value was 0.78.

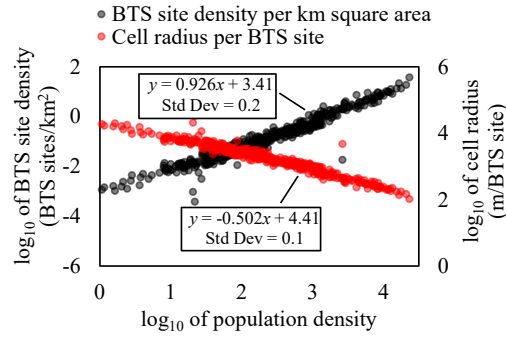


Figure 3-11. Density and cell radius of BTS site in Indonesia.

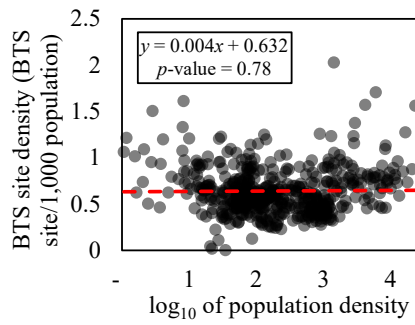


Figure 3-12. BTS site density per 1,000 people in Indonesia.

Then, $sitecount_m$ was decomposed by $TP_{y,m}$ obtained from the Dirichlet regression shown in Figure 3-6 to determine $NS_{y,m}$ as shown in (3-2). The composition of the stock of 173,886 BTS sites in Indonesia is presented in Appendix B. Figure 3-13 shows the composition of BTS sites quantified by aggregating for the six Indonesian islands or the archipelago. Currently, ~90,000 sites are deployed in the Java archipelago, with site proportions other than Macro (including the hub) accounting for 10%. Macro (including the hub) sites (>95%) were more dominant in the other archipelago.

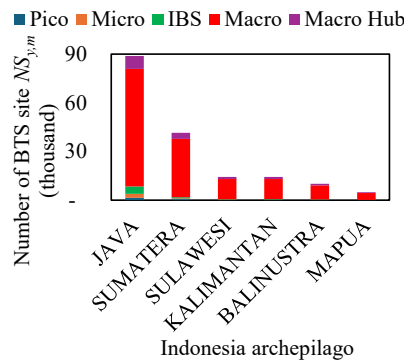


Figure 3-13. Indonesian national stock of the BTS site $NS_{y,m}$.

According to Appendix B, the Jawa Barat province leads the BTS site deployment, followed by Jawa Timur and Jawa Tengah. These regions are densely populated with considerable industrial

activity and cover a large area that requires extensive telecommunications infrastructure. However, population density plays a more significant role than land size in BTS site deployment. For example, although the DKI Jakarta province is only one-fifth the size of Lampung, the number of BTS sites in DKI Jakarta has doubled because of its higher population density and socioeconomic activity. Figure 3-14 depicts the IBS site proportion across 38 provinces in Indonesia. Of the 6,136 IBS sites estimated by our model, the Java region, Sumatera, and rest of the regions account for 76%, 11%, and 1%–4%, respectively. The dominance of IBS sites in the Java region indicates a higher level of development and a larger population than in the other regions.

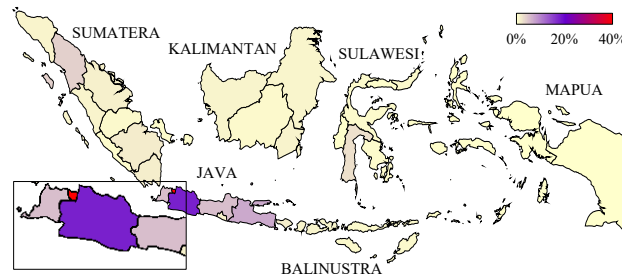


Figure 3-14. IBS site proportion across 38 provinces in Indonesia.

3.3.3.3 BTS Site Stock Power Consumption (P_{stock_t})

Figure 3-15 shows the hourly power consumption for the BTS site stock P_{stock_t} in Indonesia, aggregated by the number of sites in each municipality. According to (3-1), Indonesia's average total daily energy demand of the BTS site stock was 14.7 GWh/day or 613.5 MW, equivalent to 84.7 kWh/day and 3.5 kW per BTS site. BTS sites in the Java region represented >51% of the energy demand, totaling 8.4 GWh/day. The Sumatera region accounted for 24% of the total energy consumption due to its geographical size and increasing economic activity. Moderate-consumption regions, such as Kalimantan, Sulawesi, and Balinustra, accounted for 6%–8% of the total energy consumption because of a mix of semi-urban and rural areas. Remote regions, such as Mapua, with limited infrastructure and small populations, accounted for only 3% of total energy consumption.

Indonesia's telecommunication network's total energy demand was estimated to be 5.37 TWh/year or 1.96% of the national electricity consumption in 2022. Figure 3-16 presents a comparison of the annual electricity consumption of cellular networks with the national electricity demand. Our model's results were compared with the reported values from Indonesia's telecom operators [35, 36, 37, 38], Japan [38], Europe [39], and the world average [49]. The MED-CTN model suggested that Indonesia's actual energy consumption was 28% higher than that reported by telecom operators.

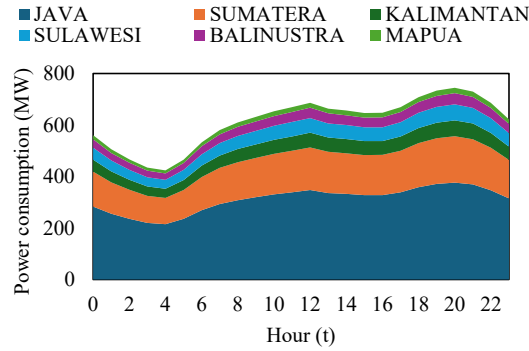


Figure 3-15. Indonesia BTS site stock's daily power consumption.

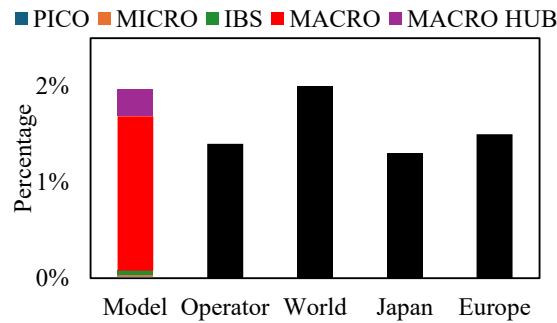


Figure 3-16. Power consumption share of BTS sites of national electricity demand comparison.

3.4 Discussion

3.4.1 Energy Demand of Indonesian BTS Site Stock

The energy consumption of Indonesia's cellular telecommunication network was estimated to be 5.37 TWh/year, which was equivalent to 1.96% of the national electricity consumption. On average, 613.5 MW represents 11% of the commercial sector's consumption, the classification category of telecom operators in the reports by the National Electricity Company [50]. As shown in Figure 3-16, the Macro BTS sites (including Macro hubs) dominates the total consumption, accounting for 96%. The proportion of IBS, Micro, and Pico BTS sites is <3%. Figure 3-6 indicates that IBS sites are primarily located in densely populated areas, particularly those exceeding 15,000 people/km². This trend reflects a network deployment strategy that prioritizes the expansion of indoor coverage networks in densely populated areas with high levels of industrial and commercial activity (Figure 3-14).

The estimated total energy consumption was 28% higher than that reported by the operators (Figure 3-16). Several factors could explain this discrepancy. First, the model assumed that all BTS sites were connected to the grid, which was not the case particularly in rural areas. Second, the absence of standardized data collection protocols between telecom operators and utility companies led to an underestimation of energy consumption. The BTS site sample dataset in our model was built in 2022

and reflects the current network conditions of that time. It includes various site types, configurations, and regional characteristics to capture the diversity of the telecommunication infrastructure. The validity of the dataset was confirmed using a verification process involving key stakeholders, including representatives from the Ministry of Communication, a telecom operator, an equipment vendor, a utility company, and a contractor, conducted as part of a research visit and an on-site survey.

In the interview with the telecom operator's representatives, they highlighted the NE proportion shown in Table 3-2, which emphasized the multilayer frequency spectrum utilization in most BTS sites. Their efforts indicated a commitment to enhancing network capacity and coverage in response to increasing user traffic. BTS consumed a base "static" power to remain operational, while an additional "dynamic" power component increased approximately in proportion to the volume of data traffic handled (Figure 3-9). The increased data traffic led to a higher energy consumption of active BTS components due to processing and transmission, leading to power consumption peaks during busy hours. Figure 3-15 shows that the hourly pattern was consistent among the regions, indicating that daily human activity and network usage patterns were similar at the aggregated level. However, the variations in the thickness of each color band revealed differences in infrastructure density, economic activity, and network load across regions.

3.4.2 Methodological Contribution of The Proposed Framework

The case study demonstrated that the proposed framework-based model fulfilled the requirements listed in the related works section. The total energy demand of the Indonesian BTS site stock was transparently quantified. The model represented the composition of BTS site types and their spatial variation, enabling the decomposition of energy demand according to municipality and BTS site type. The development of BTS site archetypes based on the sample data enabled the representation of BTS site stock with a limited number of detailed models considering the physical and technical characteristics of these sites. The archetypes representation considered various BTS site types and temporal characteristics of energy demand. The archetypes could be extended to consider HRES because of the model's capabilities. Thus, the knowledge of the energy demand of the Indonesian BTS site stock was enhanced, as discussed in the previous subsection.

Although the site-level dataset was sufficiently large to represent the BTS site features, it was not representative of the overall BTS site stock in Indonesia. Extending observations from the sample to the national level may introduce error due to substantial development disparities across Indonesia, as illustrated by the higher concentration of IBS sites on Java Island (Figure 3-13). For instance, the use of the current coarse-grained approach, which considered only the site type proportion based on the sample shown in Figure 3-3 without accounting for the spatial differences in the BTS site stock, underestimated the energy demand by as much as 4%. The scale of error may increase when HRES is considered. The use of *sitcount* data and the application of the Dirichlet regression model developed

using the sample data of 20 municipalities contributed to overcoming this issue as the socioeconomic features were considered in estimating the BTS site stock composition for each Indonesian municipality. The Dirichlet regression model represented Indonesian municipalities well because the 20 municipalities included diverse rural and urban municipalities.

Furthermore, we selected widely available socioeconomic variables as predictors. This enabled the application of the developed models to municipalities as the Dirichlet regression effectively illustrated the relationship between a municipality's population density and the stock proportion of BTS sites (Figure 3-6).

Compared with Dinata et al. [40], who estimated 12.7 TWh/year of Indonesia's cellular network energy demand, this study calculated a value that was 58% lower. This difference could be attributed to the fact that the previous study did not consider the spatial differences in the BTS site stock and did not use the BTS site as the modeling unit. BTS site counts must be adjusted at the stock aggregation step for accurate estimations because each site type has distinct peak power and power factor characteristics. This step reduces the risk of over- and underestimation of the energy demand and highlights the significant effect of population density on the site type proportions in a municipality.

3.4.3 Model Applicability to Other Region

The developed framework can be applied to other regions by adjusting the modeling methods of each component. The original BTS site archetypes could be developed by collecting the BTS site sample data, as in this study. In addition, because our archetypes cover the major BTS site types; the features listed in Appendix A can be applied where BTS site sample data are not available. The physical and technical characteristics of the BTS site considered in this study are relevant to other countries with similar characteristics. The BTS site stock can be modeled as demonstrated in the case of Indonesia, where similar data are available. In the absence of such data, the number and type composition of BTS sites can be estimated using the regression approach illustrated in Figure 3-11 and Figure 3-12 in combination with the Dirichlet regression model. This study revealed that a BTS site stock composition analysis using universally accessible information, such as population density, enabled the proposed model's application beyond the sampled regions upon necessary adjustments. As population density increases, the deployment of BTS sites becomes denser, resulting in a higher number of BTS sites per square kilometer. Based on the detailed decomposition of the dense urban, urban, suburban, and rural density categories [32], the average coverage radii of BTS site cells were approximately 100 m, 600 m, 1,100 m, and 4,200 m, respectively. Meanwhile, the average densities of BTS sites per square kilometer were 14, 2.3, 0.3, and 0.05 for each category, respectively.

3.4.4 Limitations and Future Works

Our model did not consider the annual changes in BTS site deployment. The projected annual growth rate of 20% until 2029 [3] makes evaluating the future energy demand critical. Spatio-temporal

modeling of BTS site development, including future projections, is needed to address this issue. Furthermore, the variation in the seasonal power consumption of air conditioners at the Macro Hub sites might be an underestimation because we used the *btslog* observed for four months. Further analysis is required because the energy demand of these sites is relatively large (Figure 3-16). Future work should explicitly consider air-conditioning units in the BTS site archetypes to analyze how meteorological conditions and operator strategies— such as scheduling, temperature adjustments, and passive cooling— affect overall energy demand. This will require the collection of yearly *btslogs* alongside with meteorological data to capture seasonal variability. Also, it is important to thoroughly evaluate the uncertainty of input parameters in the future energy demand calculations. In addition to the Dirichlet regression model for $TP(y_i|V_m)$, alternative methods must be examined.

Moreover, the proposed framework is capable of accommodating HRES by assessing the availability and potential capacity of renewable sources based on the physical characteristics and stock composition of BTS site archetypes. In an interview during research visit, telecom representatives mentioned that the integration of telecom sites with renewable energy is one of the strategies for mitigating the rising operational costs and environmental effects of the industry’s growing energy footprint. Future research directions must encompass not only the technical aspects of the HRES but also the economic and policy dimensions to accelerate the clean energy transition and effectively foster sustainability in the implementation.

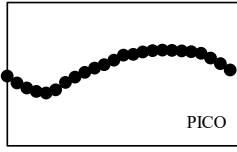
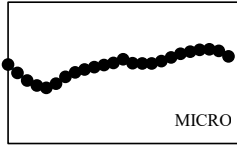
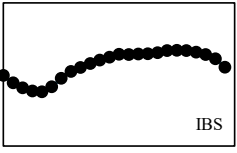
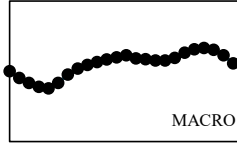
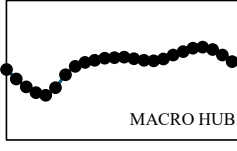
3.5 Conclusion

This study presented a macro-level framework for calculating the energy demand of cellular networks. The developed model estimated Indonesia’s total daily energy demand for the BTS site stock to be 14.7 GWh/day, averaging ~84.7 kWh per day per site, with the Java region accounting for 51% of the total energy demand. This represented an annual requirement of 5.37 TWh/year, which accounted for 1.96% of the country’s total electricity usage in 2022. The results demonstrated that the proposed framework fulfilled the following three requirements for a robust energy demand model: (1) scalability to the BTS site stock level, (2) incorporation of stock composition and representative site characteristics, and (3) applicability to other regions. The model represented the integration of stock composition alongside the representation of BTS sites, demonstrating the spatiotemporal decomposition features of energy demand. Herein, the representation of a BTS site through archetype development is relevant to similar regional contexts, particularly neighboring Asian countries. Furthermore, our model used universally accessible information, such as population density, as a predictor in the BTS site composition analysis, ensuring its applicability to other regions, even those with little available data. Leveraging the existing BTS site archetypes for future HRES implementations is vital as a mitigation strategy to improve cost efficiency, particularly in a market where telecommunications revenue growth has plateaued. Prioritizing innovative energy solutions

enables the identification of new opportunities and the reduction of operational costs, thereby supporting more sustainable and resilient business practices.

3.6 Appendix

3.6.1 Appendix A. BTS Site Archetype Characteristics

Archetype	Site type y	P_{peak_y} (kW)	Power factor $PF_{y,t}$	Equipment cabinet	Ant. Height (m)	Deployment	Avg. site area (m ²)	Physical appearance $physic_y$
Type 1	Pico	2.4		Mounted	2–5	Retail, shopping area, Roadside unit (RSU)	2–5 (max for pole)	
Type 2	Micro	2.1		Mounted	5–10	RSU, building façade, Grid pole	2–5 (max for pole)	
Type 3	IBS	2.5		Indoor	3–5 (ceiling)	In-building system with DAS	50*	
Type 4	Macro	4.2		Outdoor	20–35	Greenfield or rooftop (outdoor)	50–130	
Type 5	Macro Hub	6.7		Indoor	35–50	Greenfield (shelter) + air cond.	130	

* Assumed as a maximum spatial leasing on the building roof

3.6.2 Appendix B. BTS Site Stock $NS_{y,m}$ in Indonesia for Year 2022

No.	Archipelago	Province	BTS site type					TOTAL (site)
			PICO	MICRO	IBS	MACRO	MACRO HUB	
1	JAVA	JAWA BARAT	467	642	1,086	25,394	2,792	30,381
2	JAVA	JAWA TIMUR	266	296	422	16,470	1,764	19,217
3	JAVA	JAWA TENGAH	219	232	319	14,021	1,491	16,281
4	JAVA	DKI JAKARTA	300	942	2,474	6,737	929	11,383
5	JAVA	BANTEN	145	198	322	7,461	834	8,960
6	JAVA	D.I. YOGYAKARTA	38	45	67	2,283	246	2,679
7	SUMATERA	SUMATERA UTARA	141	160	233	8,705	931	10,169
8	SUMATERA	SUMATERA SELATAN	73	74	97	4,871	513	5,628
9	SUMATERA	RIAU	69	63	79	4,894	508	5,613
10	SUMATERA	LAMPUNG	66	67	88	4,373	461	5,055
11	SUMATERA	ACEH	47	45	57	3,325	346	3,820
12	SUMATERA	SUMATERA BARAT	47	45	56	3,299	344	3,791
13	SUMATERA	JAMBI	32	29	35	2,324	240	2,659
14	SUMATERA	KEP. RIAU	26	25	31	1,798	188	2,068
15	SUMATERA	KEP. BANGKABELITUNG	17	16	20	1,214	126	1,392
16	SUMATERA	BENGKULU	16	16	20	1,144	119	1,316
17	KALIMANTAN	KALIMANTAN TIMUR	47	44	56	3,328	347	3,822
18	KALIMANTAN	KALIMANTAN BARAT	48	47	61	3,249	340	3,744
19	KALIMANTAN	KALIMANTAN SELATAN	45	46	62	3,030	319	3,502
20	KALIMANTAN	KALIMANTAN TENGAH	31	28	34	2,244	231	2,567
21	KALIMANTAN	KALIMANTAN UTARA	8	8	9	588	61	674
22	SULAWESI	SULAWESI SELATAN	94	106	153	5,843	624	6,821
23	SULAWESI	SULAWESI UTARA	28	27	35	1,885	198	2,173
24	SULAWESI	SULAWESI TENGAH	26	23	28	1,890	195	2,163
25	SULAWESI	SULAWESI TENGGARA	20	19	23	1,450	151	1,663
26	SULAWESI	GORONTALO	10	9	12	671	70	773
27	SULAWESI	SULAWESI BARAT	9	8	10	627	65	717
28	BALINUSTRA	BALI	60	65	89	3,761	402	4,378
29	BALINUSTRA	NUSA TENGGARA BARAT	42	43	59	2,771	293	3,208
30	BALINUSTRA	NUSA TENGGARA TIMUR	31	28	36	2,167	225	2,487
31	MAPUA	MALUKU	12	11	13	863	89	987
32	MAPUA	PAPUA	10	9	11	697	72	798
33	MAPUA	MALUKU UTARA	8	8	9	595	62	682
34	MAPUA	PAPUA BARAT DAYA	6	6	7	455	47	521
35	MAPUA	PAPUA PEGUNUNGAN	6	5	6	410	42	469
36	MAPUA	PAPUA TENGAH	6	5	6	410	42	469
37	MAPUA	PAPUA BARAT	5	5	6	387	40	443
38	MAPUA	PAPUA SELATAN	5	4	5	362	37	414
TOTAL			2,525	3,446	6,136	145,996	15,783	173,886

4 Scalable Integration of Hybrid Renewable Energy System for Cellular Telecommunication Networks

4.1 Purpose

The final research stage in this dissertation aims to fill the gap for macro-level HRES implementation analysis in cellular telecommunication networks by developing a framework to integrate HRES generation supply to meet the energy demands of the BTS site network, scalable from the site to the national level. The proposed framework integrates two novel approaches: 1) synthetic BTS site stock—a modeled representation of BTS sites—in which the location, types, renewable energy potential, and technical and physical attributes are assigned based on the spatial distributions and statistical models derived from BTS site samples; 2) BTS site archetypes approach—representation of technical and physical characteristics variation of BTS sites network—adopted to simulate energy demand, along with the generation and operation of HRES, while evaluating their performance. The proposed framework incorporates geographical and meteorological data derived from a synthetic stock model to create HRES archetypes that consider different site characteristics, renewable energy potential, and spatial constraints. Additionally, it evaluates the technical and economic feasibility of HRES systems compared with that of the existing systems before it is integrated into a large-scale network. The proposed framework was validated through a case study of the BTS sites in Bali Province, Indonesia.

4.2 Methodology

4.2.1 Proposed Framework

Figure 4-1 depicts the proposed framework for the scalable integration of HRES to satisfy the demand of cellular telecommunication networks. This approach enables site-level assessments that are scalable at regional/national level, facilitating improvements in the BTS site energy efficiency from a macro-level perspective. The proposed model combines the synthetic BTS site stock and BTS site archetypes, evaluating the design and techno-economic feasibility of incorporating the HRES into the operational energy balance of BTS sites.

Section (i) of Figure 4-1 depicts a synthetic spatial distribution that represents the BTS site stock at the macro-level for the selected region. The total number and type composition are determined using a statistical model corresponding to the socioeconomic factors that reflect the actual cellular network of the region, with spatial distribution density references obtained from BTS site samples [14]. Each synthetic BTS site is assigned a random location within the designated area, enabling renewable energy resources to be allocated based on regional geographical and meteorological conditions. The synthetic distribution of the BTS site stock is required only when the actual location

data are unavailable. In cases where a BTS site sample is missing, the base layer map for the synthetic BTS site is created using predefined criteria, based on the assumptions derived from typical BTS implementations and expert insights. Alternatively, publicly available cellular coverage maps (e.g., cellmapper.net, nperf.com) can be converted into spatial density maps; however, this reduces the resolution.

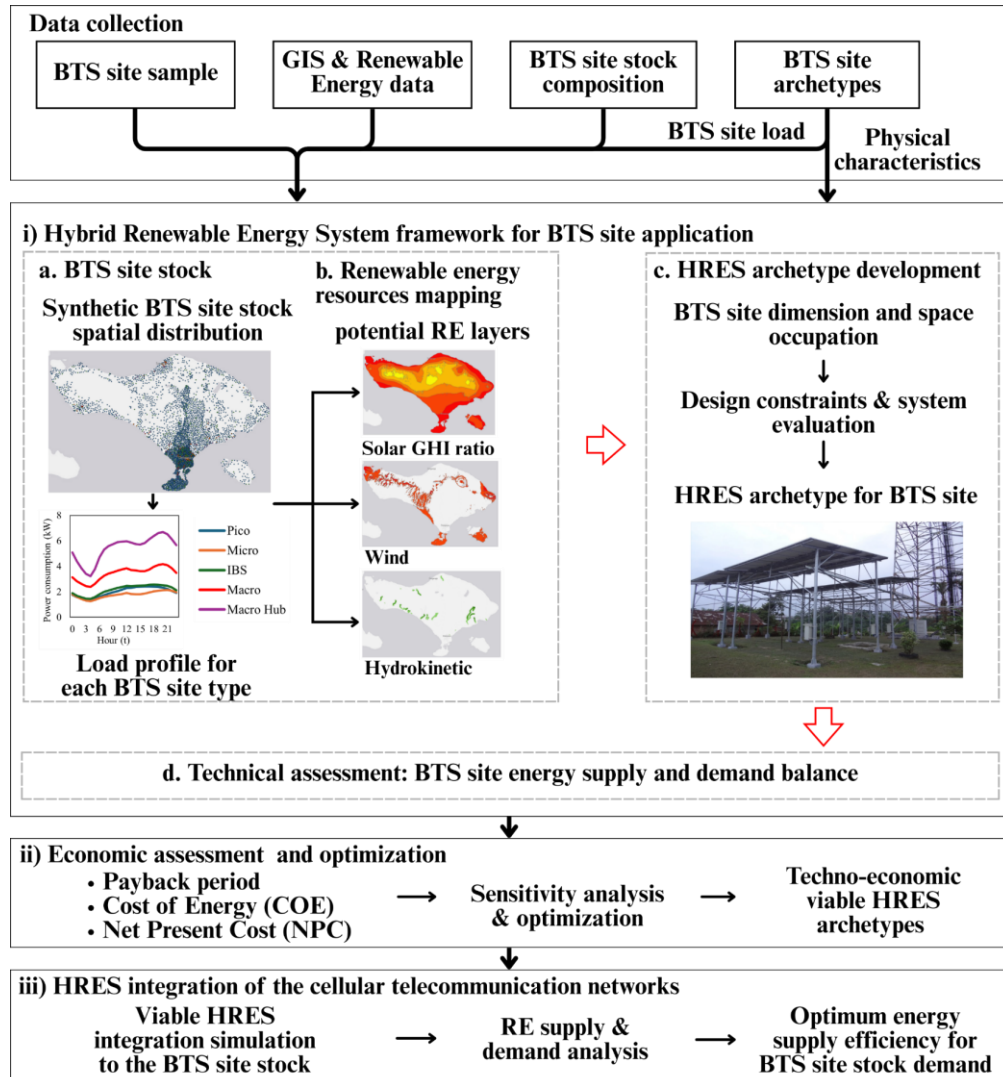


Figure 4-1. Scalable HRES integration for cellular telecommunication network framework.

Power consumption, along with technical and physical characteristics of the BTS site archetype, is attributed to each synthetic BTS site. The characteristics of these sites, combined with renewable energy data, are categorized by type to develop the HRES archetype. The spatial constraints, including site dimensions and space occupation for each archetype, are derived from the survey samples of the BTS site, facilitating equipment selection and capacity assessment. The HRES archetype is technically assessed. Various BTS site type operations integrated with HRES were analyzed alongside the

existing energy supplies, including battery, DG, and grid, to balance the energy demands and battery charging requirements. The energy generation potential from HRES was calculated considering the operation of battery and DG.

The viable HRES configurations were selected through an economic assessment, by optimizing sensitive parameters, as shown in section (ii) of Figure 4-1. The performance of the economic indicators for each HRES archetype was compared with that of the existing BTS site configuration (baseline). Additionally, the effect of varying sensitive parameters on the economic performance was examined. The integration of the only viable techno-economic HRES across the BTS site stock in the region was simulated, as outlined in section (iii) of Figure 4-1. Lastly, the performance of the HRES stock, along with the aggregated CO₂ and cost reduction, was quantified.

4.2.2 Case Study Context

4.2.2.1 Synthetic BTS Site Stock Spatial Distribution

a. Regional BTS Site Stock

Figure 4-2 shows the municipality-level of BTS stock provided by the Ministry of Communication and Digital Affairs (2022) for Bali Province. The continued deployment of 2G BTSs is essential to support legacy services, with at least one required at each site. In contrast, 3G BTSs are being phased out. 4G BTS remains the dominant technology for cellular networks in Bali, with a total of 11,500 BTS, as 5G rollout is still very limited. In [14], a statistical model was developed to quantify the BTS site stock in the region, $NS_{y,m}$, considering population density and 4G BTS stock. It comprises five different site types, y : pico, micro, IBS, macro, and macro hub, with municipalities, m , as the unit of spatial resolution. All the BTS sites in this study were on-grid, as Bali has achieved 100% electrification.

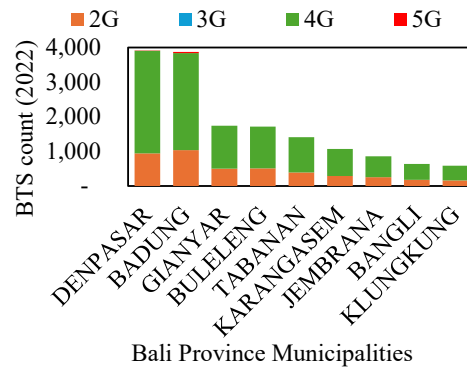


Figure 4-2. BTS stock in Bali province in 2022.

Table 4-1 summarizes the additional data utilized in this study. Data on approximately 37% of the BTS site samples from the 2022 stock in Bali Province were collected to characterize BTS site archetypes originally developed in [14] (Appendix A) for energy demand modeling. The BTS site sample includes location coordinates for 1,600 macro (and hub) BTS sites operated by two of four

telecom operators in Indonesia. Additionally, samples of battery capacity distribution for each type of BTS site were collected. Appendix B presents the battery capacity distribution obtained in the BTS site sample, detailing capacities across various BTS site types. Telecom operators prefer lithium-ion batteries owing to their compact size and low maintenance. Geographic and meteorological Geographic Information System (GIS) layers and data were incorporated for geoprocessing assessment. The geographical data layer was obtained from the Bali government website, whereas the meteorological data were sourced from NASA, the Global Solar and Wind Atlas, and other academic references. To ensure accurate representation, the BTS site dimensions and deployment were evaluated based on international and local mayoral regulations.

Table 4-1. Primary data collection

No.	Data collected	Details
1	BTS site sample	Actual BTS site location coordinates in Bali Province to analyze their spatial distribution.
2	Battery capacity sample	Over 6,600 samples from the BTS site samples dataset, indicating the typical capacity for each BTS site type.
3	Regional geographical data	Geographical Information Systems layer data, such as regional borders, exclusion/inclusion areas, and elevation [51].
4	Regional meteorological data	Global Horizontal Irradiance (GHI) index [52], Wind speed at 100 m height [53], Bali province river stream velocity [54].
5	Tower site deployment standards and regional regulations	References for BTS site deployment: • Structural Standard for Antenna Supporting Structures (ANSI/TIA-222-G). • Regulation of Mayor No. 10 of 2022 regarding the location regulations for constructing telecommunications towers in Indonesia.

b. Setting of HRES

This study selected Bali Province, a representative region of Indonesia, to demonstrate the integration of HRES for cellular telecommunications networks. Table 2 summarizes the HRES setting and highlights equipment selection for three renewable energy sources with the highest potential in Indonesia: solar, wind, and hydrokinetic energy [13]. It also presents design constraints for each deployment type to guide the selection of suitable renewable energy sources based on the BTS site archetypes in Appendix A.

The type of BTS site deployment is a critical factor in prioritizing renewable energy configurations, especially when several viable options exist. While the constraints for greenfield and pole sites are clear, this study considers the priority for rooftop sites as wind (WT), solar (PV), and hydropower (MH), with wind preferred for its effectiveness at higher elevations and hydropower least due to higher transmission loss risk. Battery capacity data samples were included to reflect backup practices.

Table 4-2. HRES setting summary

Site type	Site deployments and design constraints	Renewable energy equipment selection
Macro & Hub	Greenfield (G) • Ground-level BTS site construction. • Sufficient space is available to combine two	Solar Photovoltaic (PV) • SunPower E20-327Wp • Module efficiency: 20.4% • Area to capacity conversion: 218 W/m²
	Rooftop (R) • Antenna and BTS installation on building roofs. • Spatial constraints restrict implementation to a single renewable energy source. • Permitting requirements and limited site accessibility.	Wind turbine (WT) • AEOLUS V-1 kW (vertical axis) • Cut-in wind speed: 3 m/s • Area to capacity conversion: 100 W/m²
IBS		Micro Hydrokinetic Turbine (MH) • SMART Monofloat Turbine • Capacity: 5 kW
Micro	Pole (P) • BTS and antenna are attached to the pole.	• Min river depth: 2 m
Pico	• Compatible only with solar renewable energy source.	• Area to capacity conversion: (not needed)

4.2.2.2 Techno-economic Assessment

Appendix C lists the parameters utilized for techno-economic assessment. The calculation parameters were chosen to closely represent local conditions. When local data were unavailable, global average values served as substitutes. In this study, all parameters were assumed to remain constant annually throughout the system's lifetime.

4.2.3 Framework Application

4.2.3.1 Hybrid Renewable Energy System Framework for BTS Site

a. BTS Site Stock

Synthetic BTS Site Stock Spatial Distribution

Figure 4-3 depicts the method used to develop a synthetic BTS site stock using geoprocessing tools, subject to the availability of BTS site samples. First, the number of BTS sites stock in the region was calculated based on the method in [14]. Telecom operators may install up to four BTS units at a single site under different frequency licenses. Therefore, the proposed framework used BTS sites as the modeling unit, rather than the BTS itself. This approach is essential as the energy consumption is measured at the BTS site level. The 4G BTS stock in Figure 4-2 was converted into the number of BTS sites, $sitcount_m$, using a 0.38 scale factor [14]. The variation in the composition of the BTS sites, $TP_{y,m}$, corresponded to municipal socioeconomic factors, which was identified from the Dirichlet regression. Subsequently, the $sitcount_m$ was decomposed by $TP_{y,m}$ to determine BTS site stock in the region $NS_{y,m}$ [14].

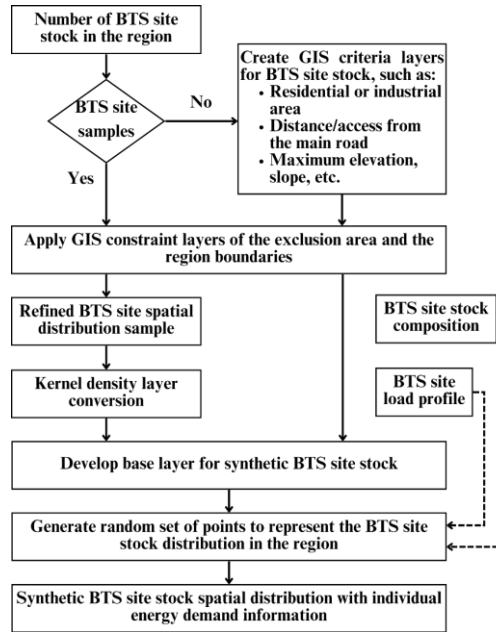


Figure 4-3. Synthetic BTS site stock generation method using the geoprocessing tools

In case available, the BTS site sample from the stock was checked to ensure that it lies outside the prohibited or protected areas, using exclusion zones and region boundary layers in the geoprocessing tools. Water bodies, cultural and conservation forests, and national parks were excluded from the synthetic BTS site stock and renewable energy mapping. Subsequently, the refined BTS site distribution sample was transformed into a kernel density map, which served as a base map to indicate the area where synthetic random points were generated. The density reference of these points was based on the density value obtained from the BTS site sample distribution, whereas the total number of points generated was manually set, referencing $NS_{y,m}$.

As a spatial sample for IBS, micro, and pico BTS site types was not obtained, the base map for the synthetic distribution was generated using the following criteria: 1) a maximum distance of 1 km from the main road, 2) located in a residential area, and 3) an elevation of less than 100 m above sea level. Each criterion was represented as a GIS layer, and all three layers were then clipped together to create a designated area layer for IBS, micro, and pico BTS sites. The criteria were determined assuming that IBS, micro, and pico BTS site implementations were categorized as urban (with a population over 1,000) or densely urban (with a population over 10,000) [32].

b. Renewable Energy Resource Mapping

The synthetic BTS distribution was then overlaid with the renewable energy resources potential layer, sequentially. The synthetic BTS site layer was first overlaid with the initial renewable energy resources map. This was followed by a second overlay with another renewable energy resources map. The output from this second overlay was used as the input for the third overlay process. The final

output was a GIS layer detailing the spatial distribution of BTS sites stock in the region, geographical and meteorological data, along with the corresponding renewable energy combinations at each location.

c. HRES Archetype Development

The synthetic BTS site stock enables mapping BTS sites to renewable energy resources. In addition to the potential of renewable energy resources, the technical and physical characteristics of the BTS site archetypes (Appendix A) were attributed for supply and demand analysis. This study classified HRES archetypes by integrating BTS site types, deployment types, and configurations of renewable energy potential, as detailed in the setting of HRES section. BTS site types represent overall sites characteristics. BTS site deployments indicate spatial constraints, including site dimensions and space occupation. The identification of site dimensions and space availability significantly affects the HRES design process, particularly in determining the equipment and support structures. The BTS site's deployment was analyzed using the Street View feature of Google Maps and aerial imagery to assess the overall dimensions of the BTS site. The median value of the sample distribution was selected to determine the single dimension representation of the deployment of each BTS site. Furthermore, renewable energy configurations were selected and prioritized according to site deployment design constraints.

Figure 4-4 depicts a deployment of PV HRES to a BTS site with greenfield, rooftop, and pole deployment. Equipment selection considered dimensions and module efficiency as detailed in the case study context (Table 4-2). For pole, this study limits the maximum number of PV modules to three, with a total capacity of 1.02 kW. The rooftop and greenfield site equipment capacities were determined by adjusting the available space and PV structure accordingly, following an area-to-capacity conversion. The low PV structure is 58% cheaper than the elevated structure based solely on the structural components. Wind and hydrokinetic turbines were limited to one unit per site owing to the high initial costs. This consideration was also used to determine the capacity of equipment in other HRES archetypes.

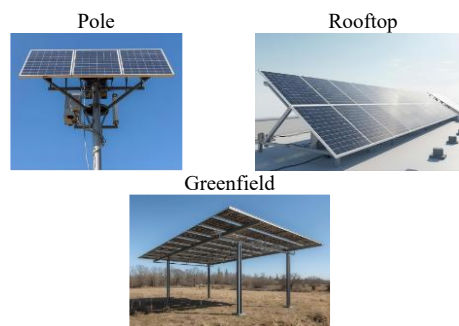


Figure 4-4. PV HRES deployment example

d. Technical Assessment: BTS Energy Supply and Demand Balance

Figure 4-5 depicts the typical operation of the electrification system for a BTS site. The baseline setup, represented by red arrows, comprised three configurations: grid + battery for on-grid sites, DG + battery for off-grid sites, and a combination of grid, battery, and DG for priority sites or areas with unreliable grid access. When HRES were integrated, as represented by the green arrow, the role of the battery shifted from serving solely as a backup to becoming a secondary energy source after renewable energy. The proposed system prioritizes the energy supply from renewable generation, followed by battery discharge and grid purchases. Under grid operation, the load was supplied while the battery was charged. DG was activated when the battery backup reached its capacity threshold and the grid was unavailable to support the load and recharge the battery.

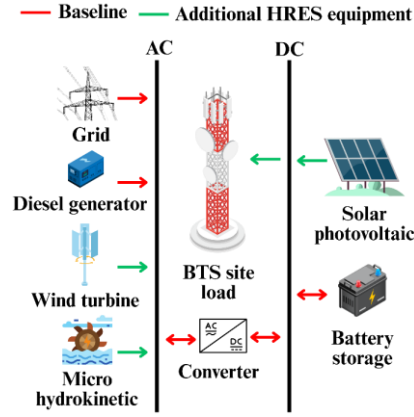


Figure 4-5. Typical BTS site electrification overview.

BTS Site Power Consumption

Each site type, y , has its own hourly t power consumption, $PC_{y,t}$, and technical and physical characteristics (Appendix A). The variation in the power consumption for each BTS site type is primarily, but not solely, attributed to the different coverage radii. For example, a macro BTS site with a coverage of up to 30 km [14] required a substantial amount of power owing to the increased traffic from its extended coverage. Conversely, the macro hub exhibited a higher power consumption than the other types owing to the larger amount of installed equipment and air conditioning units. As per the energy demand model [14], $PC_{y,t}$ was quantified as $PC_{y,t} = P_{peak_y} \times PF_{y,t}$, where P_{peak_y} denotes the peak power consumption for site type y , and $PF_{y,t}$ represents the hourly power factor that accounts for temporal variation in power consumption (Appendix A).

Renewable Energy Generation Potential

The energy generation potential from each HRES was calculated based on the suitable renewable energy combination at each location. First, the potential energy generation of each renewable energy source was calculated, as expressed in (4-1)–(4-3). This calculation considered the availability of

space at the BTS site, equipment capacity, and the monthly average temporal resolution of solar irradiation, wind speed, and river flow velocity. It was assumed that the renewable energy potential would remain constant throughout the project's lifetime and that long-term climate variability was not considered. The results of each calculation were then summed to provide the total renewable energy generation at that site.

Solar Photovoltaic (PV)

The daily PV output power, P_{PV} , was estimated considering hourly solar irradiance GHI data for the Bali region, as shown in (4-1). The total PV panel area, A_{PV} , was determined based on the BTS site space availability, whereas η_{PV} corresponds to the PV module efficiency, and the system efficiency η_{sys} accounts for the converter losses [20, 49, 50, 51].

$$P_{PV} = GHI \times A_{PV} \times \eta_{PV} \times \eta_{sys} \quad 4-1$$

Wind Turbine (WT)

The wind turbine output power, P_{wind} , in (4-2) was estimated as half the product of the air density, ρ_{wind} , rotor swept area A_{rotor} , and the cube of wind speed, v_{wind} , scaled by the power coefficient, $CP_{turbine}$ [58]. This study utilized the vertical axis wind turbine [59]; therefore, the swept area was defined as the height of the rotor, H , multiplied by the diameter of the rotor, D . The wind speed was obtained at a height of 100 m. To generate the minimum energy required, areas in Bali Province with a minimum wind speed of 3.5 m/s were selected.

$$P_{wind} = \frac{1}{2} \times \rho_{wind} \times A_{rotor} \times v_{wind}^3 \times CP_{turbine} \quad 4-2$$

Micro Hydrokinetic (MH)

The operating principle of hydrokinetic turbines is similar to that of wind turbines, with water density, ρ_{hydro} , and river stream velocity, v_{stream} , serving as the primary driving factors instead of wind [60]. The analysis included the technical specifications of the SMART Monofloat 5 kW system [61], as expressed in (4-3). A river was selected for each BTS site, adhering to a minimum slope contour requirement of greater than 2%. Additionally, considering transmission losses, only BTS sites located within a 500 m buffer distance from the riverside are considered for hydrokinetic potential.

$$P_{hydrokinetic} = \frac{1}{2} \times \rho_{hydro} \times A_{MHrotor} \times v_{stream}^3 \times CP_{turbine} \quad 4-3$$

Battery Storage

The utilization of batteries as primary energy sources instead of backup energy sources necessitated careful calculation of their capacities. Within HRES, the battery sizing was designed to comply with

the standards of the 6-h system average interruption duration index (SAIDI) and four interruptions per year system average interruption frequency index (SAIFI). Furthermore, the battery was intended to store the excess energy generated by renewable sources for use during the off-peak hours. The appropriate battery size was essential for minimizing the excess electricity, which occurred when the power generated exceeded the demand or storage capacity. The battery capacity, $Batt_{cap}$, to operate both functions is calculated as follows [62]:

$$Batt_{cap} = \frac{E_{load} \times Autonomy}{DoD \times \eta_{batt} \times V_{sys} \times (1 - Batt_{deg})} \quad 4-4$$

where E_{load} denotes the BTS site energy consumption, $Autonomy$ denotes the minimum duration of battery backup during power outage, which is at least 6-h in this study. DoD and η_{batt} denotes the depth of discharge and efficiency of the battery, respectively, and V_{sys} denotes the system voltage of the BTS site. The battery degradation rate, $Batt_{deg}$, represents a margin added during the sizing process to ensure that, despite long-term capacity loss due to degradation, the battery can still satisfy the required energy demand. The typical degradation for a battery lifetime of 10 years ranges from 10% to 30%, with a conservative estimate of 20% selected for this study. Battery storage is expected to minimize excess energy generation during the peak hours. Therefore, the potential surplus renewable energy generation from HRES must be added as E_{load} . The maximum charge/discharge rate of the battery in this study was 0.5 A/Ah, indicating that the maximum battery discharge power capacity accounts for only half of the battery capacity per hour.

Diesel Generator

In the present simulation, only the macro hub BTS site type used a DG; macro hub was classified as a priority as it functions as a network hub that interconnects various BTS sites. DGs are used as the final backup when all the existing electrification sources (grid, renewable energy, and battery storage) fail to satisfy the demand. Despite high costs and emissions, they remain a reliable last-resort option for system electrification; the capacity, DG_{cap} , is calculated as follows [63]:

$$DG_{cap} = (E_{load} + Batt_{power_c10}) \times smf \quad 4-5$$

$Batt_{power_c10}$ denotes the required charging power, which is one-tenth of the battery system capacity (Ah), thereby ensuring safe charging and a long battery lifetime. Additionally, the safety margin factor, smf , was applied to oversize the capacity of the DG to reduce the overload risk, minimize operational stress on the generator, and enhance both performance stability and lifetime.

4.2.3.2 Economic Assessment and Optimization

Three economic performance indicators were assessed for each HRES archetype: net present cost (NPC), cost of energy (COE), and payback period. The detailed explanation of each indicator is

provided in Appendix E as referred to in [62], [64]. A comparative analysis was conducted for each HRES archetype when compared with the baseline, and the results were evaluated for sensitivity to various parameters, including space availability, electricity prices, discounted rate, and battery capacity. A baseline acceptable payback period of 10 years was set for all the HRES archetypes, as this study considers the large-scale implementation of HRES on an on-grid BTS site. The HRES archetype was identified as a technically and economically viable solution for BTS site electrification if it outperformed the baseline.

4.3 Result and Analysis

4.3.1 Hybrid Renewable Energy System Framework for BTS Site

4.3.1.1 BTS Site Stock and Renewable Energy Mapping

Figure 4-6 depicts the stock composition of 4,378 BTS sites in nine municipalities in Bali Province. More than 85% of the site stock are macro BTS sites, whereas 9% are hub sites. The remaining BTS site stock comprises 2% IBS, 1.5% micro sites, and 1.4% pico sites.

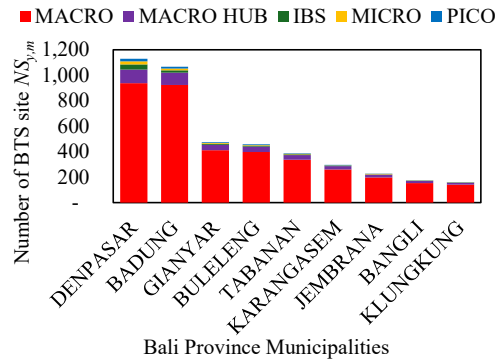


Figure 4-6. BTS site stock in Bali province.

Figure 4-7 depicts the visualization of the synthetic BTS site stock and renewable energy mapping potential in Bali Province. Figure 4-7(a) shows the reference macro and macro hub BTS site sample locations for each municipality in this study. Figure 4-7(b) depicts a kernel density base layer to generate the synthetic macro and macro hub BTS sites, developed by the sample data location. In this layer, darker-colored areas indicate higher pixel density values, indicating that more synthetic points were generated in those regions. Figure 4-7(c) depicts the predefined criteria base layer to generate the synthetic IBS, micro, and pico BTS sites. Figure 4-7(d) indicates the location of the generated synthetic BTS sites. Spatial validation involved comparing the kernel density pixel map (raster) of the synthetic points and the reference sample. Pixel-wise differences between these rasters (the subtraction raster) can be used to determine whether the synthetic distribution spatially aligns with the reference sample. Zonal statistics (mean and standard deviation) of the subtraction raster were calculated to evaluate average spatial intensity and density stability within each zone.

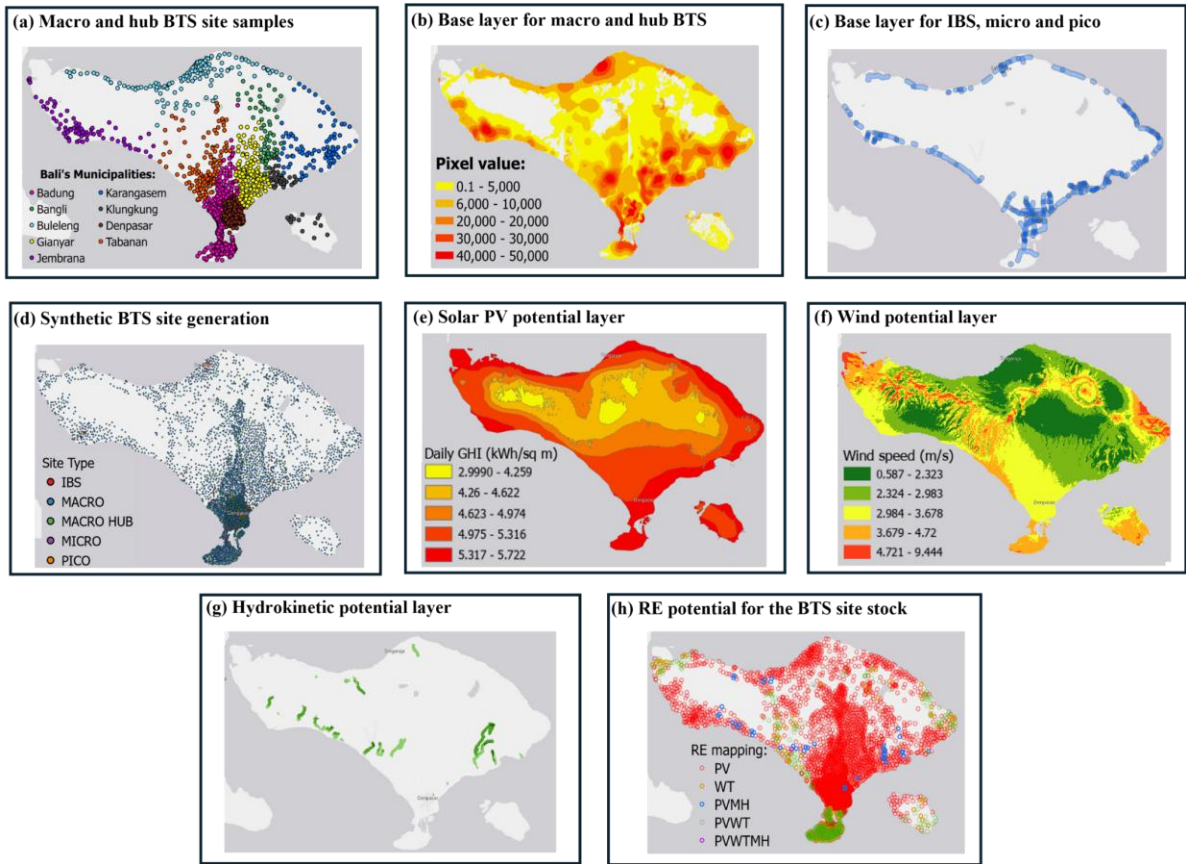


Figure 4-7. Spatial distribution of synthetic BTS site stock (a)-(d), and renewable energy mapping (e)-(h), in Bali Province.

Figure 4-7(e) shows the solar renewable energy potential available across the region, divided into five spatial zones based on the irradiation levels from 3–6 kW/m²/d [52]. Conversely, as illustrated and Figure 4-7(f) to (g), only a limited number of regions have wind and hydrokinetic resources that satisfy the minimum criteria as described in Table 4-2. Figure 4-7(h) depicts synthetic BTS site stock after being mapped with the renewable energy resource potential layer sequentially. At this stage, each synthetic BTS site was specified for renewable energy resource potential, power consumption, and other characteristics given by BTS site archetypes.

Table 4-3 summarizes the potential of the renewable energy resources for various BTS site types following the mapping process. Of the total potential, 84.4% is compatible with PV energy, 14.3% is compatible with PVWT, 1.3% is compatible with PVMH, and only one site (0.02%) supports all three combinations (PVWTMH). Aligning stock distribution with physical site locations improves the analysis quality and facilitates more informed decision-making based on reliable metrics.

Table 4-3. Renewable energy resources potential mapping for the BTS site stock in Bali Province.

Site type	PV	WT	PV-MH	PV-WT	PV-WT-MH	Total BTS sites
Macro	3,171	149	37	398	1	3,756
Macro Hub	344		4	57		405
IBS	84	7				91
Micro	65					65
Pico	61					61
Total	3,725	156	41	455	1	4,378

4.3.1.2 HRES Archetype Development

Figure 4-8 depicts the detailed BTS site deployment proportion, grouped by five BTS site types identified in the demand modeling. In total, as explained in previous section, 330 randomly selected samples were used to identify the specific area designation for each BTS site deployment, based on aerial imagery assessment. Of these, 61% were classified as greenfield sites, 32% as rooftop sites, and 6% as pole sites. Approximately 23% of the samples indicated that macro sites were installed on rooftops, rather than being deployed on greenfield sites. This highlights the varied deployment strategies for macro site installations. Regarding micro and pico BTS sites, 3% of the total samples exhibited pole installations.

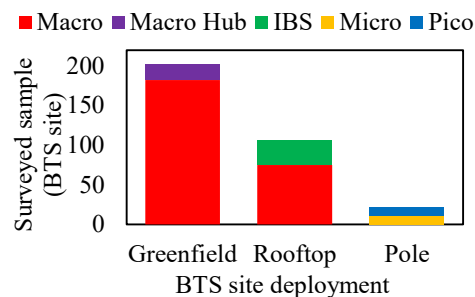


Figure 4-8. BTS site deployment type proportion of the samples.

Figure 4-9 depicts the distribution of total dimensions for greenfield and rooftop sites. For greenfield sites (a), over 80% of the samples fall within 150 m², with a median of 100 m². Conversely, rooftop sites (b) are skewed, with over 70% of the sample under 10 m², with median value of 10 m². The median value represents the single BTS site dimension of each deployment. In building system (IBS) sites, the area availability is assumed to be identical to that of the rooftop. Additionally, a pole is assumed to be a roadside unit pole with the same dimensions for all the sites.

Based on HRES archetype design, Figure 4-10 illustrates that PV HRES equipment occupies up to 70% (210 m²) of the total BTS site area of 300 m². An elevated PV support structure on greenfield sites enables the placement of PV panels above the existing BTS equipment, thereby maximizing the installed capacity. Various string configurations for the PV panels (denoted as: 2B, 2D, 9, 10, and 11)

were developed with up to 4 meters of clearance above the installed equipment cabinets (except the shelter) to maximize space utilization, achieving a space occupation scenario of up to 70%.

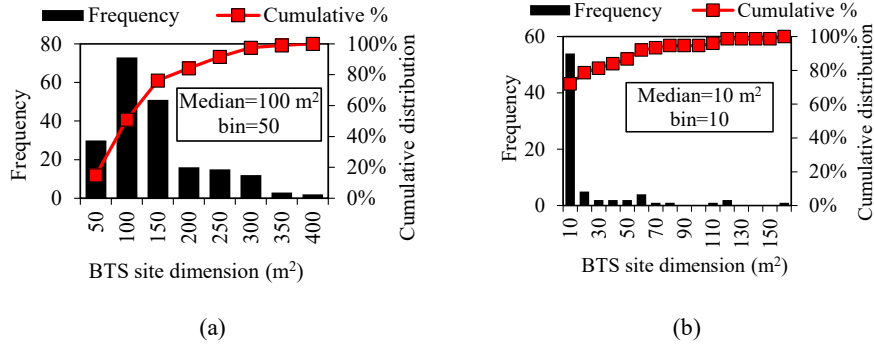


Figure 4-9. BTS site dimension sample distribution for (a) greenfield and (b) rooftop site deployment

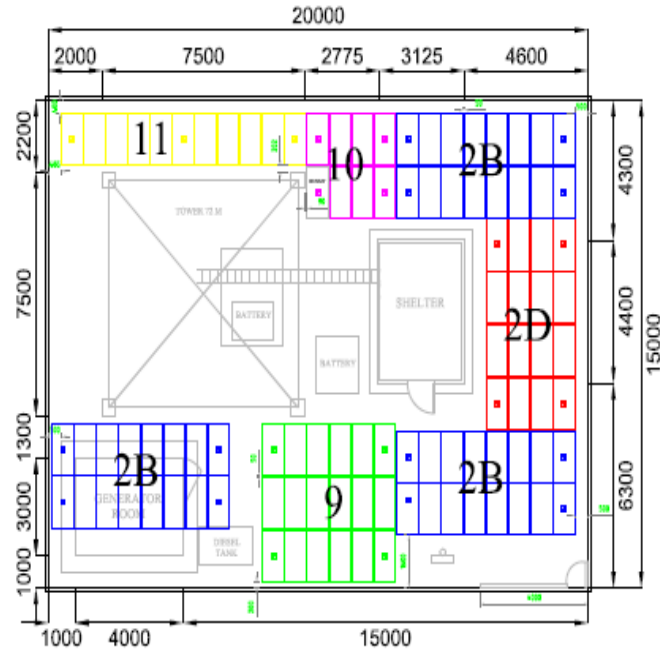


Figure 4-10. Simulation of 70% BTS site space occupation for PV equipment.

Table 4-4 lists the number of examined 13 HRES archetypes h , extending Table 4-3 by incorporating additional BTS site deployment information. Mac_G_PV is the most dominant archetype, accounting for 52% followed by Mac_R_PV with 21%, and Mac_G_PVWT with 9%. Mac_G_PVWTMH, Machub_G_PVMH (DG), and IBS_R_WT exhibit the least proportion, with 0.02%, 0.09% and 0.16% respectively. Following the area to capacity conversion in Table 4-2 for a 70% occupancy, the PV HRES installations for greenfield, rooftop, and pole deployment exhibited capacities of 14.3, 1.71, and 1.0 kW, respectively. When PV is combined with other renewable energy sources, the total capacity increases to a maximum of 21.3 kW.

Table 4-4. HRES archetypes detail

No	HRES Archetype <i>h</i>	Site type <i>y</i>	Deployment	BTS site dimension <i>n</i> (m ²)	Renewable energy sources	BTS site stock <i>NS_{y,m}</i>	HRES equipment capacity_70% space occupation (kW)	Avg. daily energy generation (kWh/d)
1	Mac_G_PV	Macro	Greenfield	100	Solar	2,261	14.3	66.3
2	Mac_G_PVMH	Macro	Greenfield		Solar, Hydro	37	21.3	70.3
3	Mac_G_PVWT	Macro	Greenfield		Solar, Wind	398	14.2	65.6
4	Mac_G_PVWTMH	Macro	Greenfield		Solar, Wind, Hydro	1	21.2	60.3
5	Mac_R_PV	Macro	Rooftop	10	Solar	910	1.71	8.0
6	Mac_R_WT	Macro	Rooftop		Wind	149	1.00	5.3
7	Machub_G_PV (DG)	Macro hub	Greenfield	100	Solar	344	14.3	66.4
8	Machub_G_PVMH (DG)	Macro hub	Greenfield		Solar, Hydro	4	21.3	72.2
9	Machub_G_PVWT (DG)	Macro hub	Greenfield		Solar, Wind	57	14.2	66.4
10	IBS_R_PV	IBS	Rooftop	10	Solar	84	1.71	8.3
11	IBS_R_WT	IBS	Rooftop		Wind	7	1.00	4.3
12	Mic_P_PV	Micro	Pole	Mounted	Solar	65	1.02	4.9
13	Pic_P_PV	Pico	Pole	Mounted	Solar	61	1.02	4.9

4.3.1.3 Technical Assessment: BTS Site Energy Supply and Demand Balance

Table 4-4 also presents the average daily HRES energy generation for each HRES archetype, which was calculated using (4-1 - 4-3). The Mac_G_PV HRES produced an average of 66.3 kWh/d, while Mac_R_PV produced 8.0 kWh/d. With a fixed capacity, the pole deployment of solar HRES achieve an average energy generation of 4.9 kWh/d. The combination of PV and MH present the highest average generation potential, exceeding 72 kWh/d, whereas IBS_R_PV provides the lowest supply with an average of 4.3 kWh/d.

Table 4-5. Battery capacity comparison for each BTS site type

BTS site type	Average load (kW)	Replacement battery capacity for HRES		Median value of existing battery	
		Battery capacity (Ah)	Battery capacity (kWh)	Battery capacity (Ah)	Battery capacity (kWh)
Macro	3.4	1,200	57.6	400	19.2
Macro hub	5.5	1,400	67.2	400	19.2
IBS	2.2	440	21.1	600	28.8
Micro	1.8	370	17.7	100	4.8
Pico	2	405	19.4	600	28.8

Table 4-5 presents a comparison of the existing battery capacity (Appendix B) and the calculated battery capacity using (4-4) for each BTS site type. Appendix B indicates that battery capacity is strongly influenced by site-specific profiles, with no clear one-to-one relationship between site type and capacity. Accordingly, the median value is used to represent the typical battery capacity for each BTS category. While the calculated requirements fall within the observed sample distributions, comparison with median existing capacities reveals that macro, macro hub, and micro sites currently have insufficient battery capacities for a 6-hours outage, while IBS and pico sites do not. A diesel

generator with a capacity of 15 kW or 18 kVA calculated can effectively support the load of the macro hub BTS site and charging the battery as per (4-5).

Figure 4-11 depicts the hourly energy balance simulation for the Machub_G_PV HRES over 24 h, comparing four battery and PV capacities scenario combinations. The simulation considers a battery capacity of 19.2 kWh for the existing system and 67.2 kWh for the replacement scenario. Additionally, two photovoltaic (PV) capacities are evaluated: 8.2 kW at 40% site occupancy and 14.2 kW at 70% site occupancy. The graph illustrates the energy pattern, where the BTS sites load is met through battery discharge, grid purchases, PV output, and DG power. Additionally, the last three resources are also used to charge the battery. A 19.2 kWh existing battery with 8.2 kW PV supplies most daytime BTS site demand but offers limited load shifting, leading to continued nighttime grid reliance. Increasing PV to 14.3 kW reduces grid consumption; however, limited storage capacity results in significant curtailment. In contrast, a 67.2 kWh battery with 8.2 kW PV enables effective evening load shifting and lowers grid purchases. The combination of 14.3 kW PV and 67.2 kWh storage maximize PV utilization, substantially reducing both grid dependence and curtailment despite increased load. DG supports loads and recharges batteries during randomly scheduled 6-hour outages that occur four times a year before peak PV generation, but do not significantly affect the energy balance for a year.

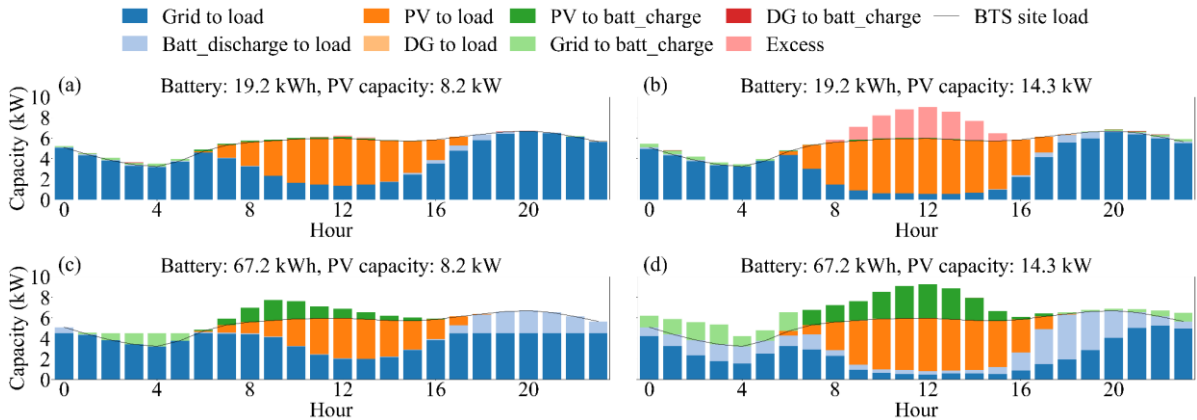


Figure 4-11. Annual average comparison of Machub_G_PV HRES hourly energy balance, featuring two battery capacities and occupancy scenarios.

Figure 4-12 compares Mac_G_PV HRES autonomy during electricity outages across four occupancy scenarios. Calculating potential PV energy generation using (4-1) allows for the inclusion of surplus energy as additional consumption E_{load} . This assesses the HRES *autonomy* as in (4-4) with a 1,200 Ah battery capacity while adhering to the parameters in Appendix C. Following the area-to-capacity conversion, occupying 70% of the BTS site space allows for a 14.3 kW PV system that generates output about 23 MWh/year (63 kWh/d) and remains operational during a 16-hour power

outage. At 40%, 50% and 60% occupancy, the capacities increase to 6 hours, 8 hours, and 8 hours of autonomy, respectively.

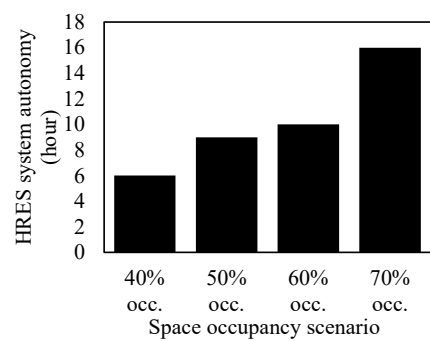


Figure 4-12. Comparison of Mac_G_PV HRES autonomy during electricity outages under different occupancy scenarios.

4.3.2 Economic Assessment

Figure 4-13 depicts the economic assessment of the NPC, COE, and the payback period across 13 HRES archetype designs, as expressed in (4-6)–(4-11). Each BTS site type has its own NPC and COE baseline owing to variations in the power consumption, existing battery capacity (Table 4-5), and grid purchases. The red dashed line represents the baseline performance.

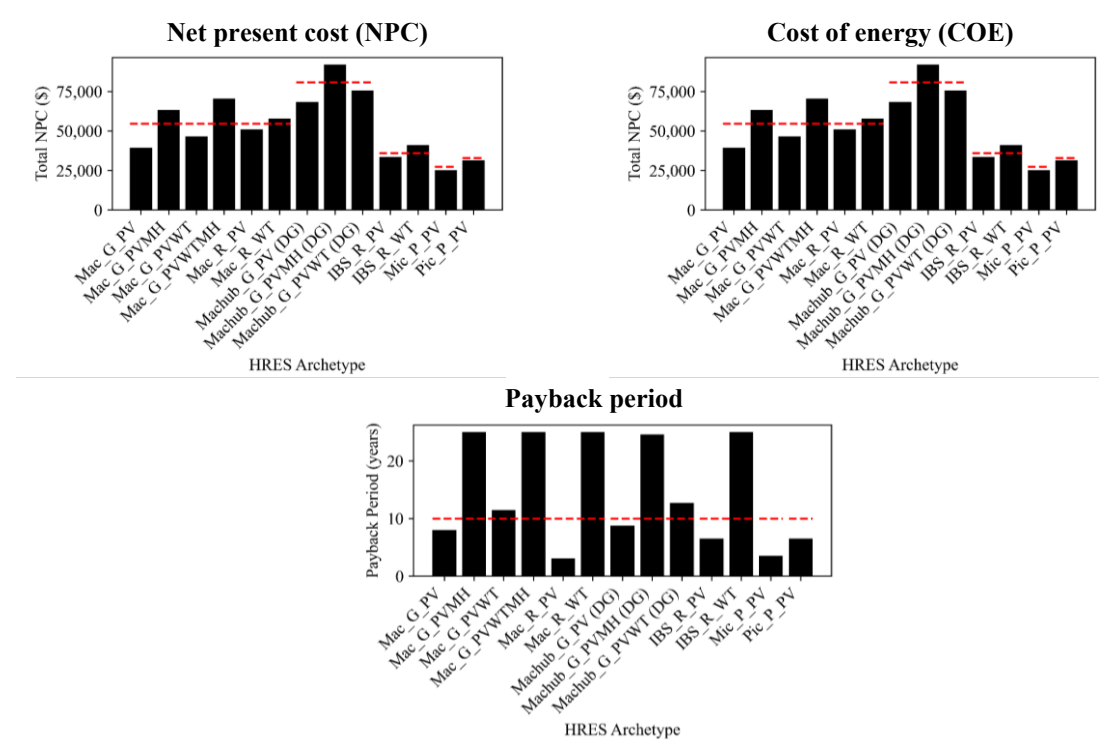


Figure 4-13. Economic assessment of HRES archetypes.

The assessment indicates that only six out of the 13 HRES archetypes perform economically better than the baseline: Mac_G_PV, Mac_R_PV, Machub_G_PV(DG), IBS_R_PV, Mic_P_PV, and Pic_P_PV. As an example, Mac_G_PV HRES exhibits a total NPC of \$39,271 and a COE of \$0.085/kWh. This is an improvement when compared with the baseline NPC of \$54,643 and COE of \$0.118/kWh. The payback period for integrating PV HRES in greenfield deployment lies between 8 and 9 years, whereas rooftop and pole deployment have a significantly shorter payback period, ranging from 3.0 to 6.5 years. Although Mac_G_PVWT archetypes exhibit better NPC and COE, the 12 years payback period making it economically unfeasible.

Figure 4-14 depicts the economic assessment with different battery capacity conditions for (a) macro and (b) macro hub BTS site types. The most economically viable battery capacity for HRES integration on the macro BTS site was selected to be 57.6 kWh and that on the macro hub site was 67.2 kWh, as shown in Table 4-5, despite an excess electricity generation of 24 kWh/year. Excess electrical power is unavailable for the IBS, micro, and pico BTS sites owing to equipment capacity limitations. This is essential for determining the battery capacity that optimally stores the renewable energy generation while ensuring economic viability, with a payback period of under 10 years.

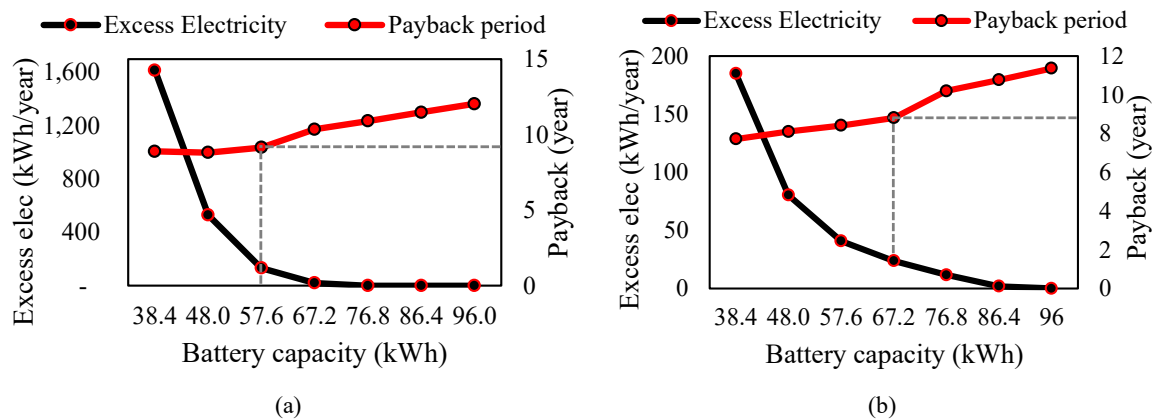


Figure 4-14. Economic assessment of battery replacement for (a) macro and (b) macro hub BTS site types.

Figure 4-15 presents a comparison of the COE across different scenarios of space occupancy and electricity prices for the Mac_G_PV HRES. By optimizing the space occupancy to 70% of the BTS site for HRES implementation, the COE was reduced when compared with the baseline configuration, regardless of the electricity price. At the current \$0.1/kWh electricity price, a 70% space occupancy shows the lowest COE. However, as electricity prices rise, a 40% space occupancy becomes more favorable. Additionally, the payback period for this system lies below the 10-year baseline, as shown in the payback period plot in Figure 4-13.

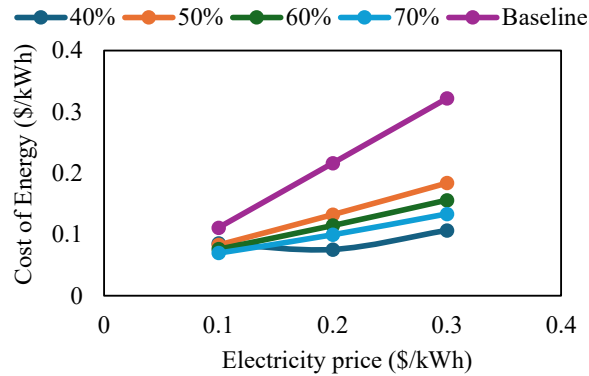


Figure 4-15. Cost of energy comparison among space occupancy scenarios.

Figure 4-16 depicts the sensitivity analysis of the Mac_G_PV HRES implementation concerning variations in electricity prices and discount rates. In scenario (a), the government's reduction of the electricity subsidy increases the price to \$ 0.3/kWh, resulting in a reduction of the payback period from 8 to 2 years, assuming a constant discount rate. In scenario (b), the government provides incentives by reducing the discounted rates to absorb risks and decrease the capital cost. The reduction in the payback period is insignificant based on the assumption of a constant electricity price of \$0.1/kWh. This result indicates that, if the electricity subsidies decrease in the future, HRES implementation will become more appealing to telecom operators.

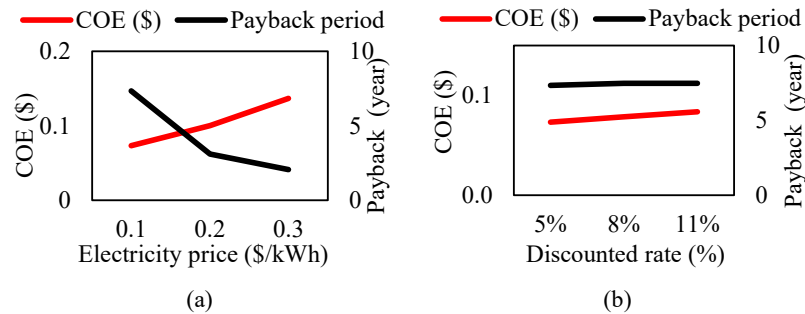


Figure 4-16. Sensitivity analysis of Mac_G_PV implementation relative to (a) electricity price and (b) discount rate.

Additionally, the economic performance of the HRES archetype was analyzed by comparing the PV support structures (see Figure 4-4). In terms of the overall system costs, the elevated PV structure incurs an additional investment of 7.4%, or approximately \$5,361, when compared with the low structure. The capital cost of the PV system per kilowatt peak is \$1,100 for the elevated and \$1,018 for the low structure. Although the low PV structure is more cost-effective, it does not significantly reduce the payback period. The payback period for the elevated structure is 9.1 years, whereas it is slightly reduced to 8.5 years for the low PV structure. Furthermore, the elevated structure helps in maximizing the space occupancy of the BTS site up to 70%, as shown in Figure 4-10.

4.3.3 HRES Integration of the Cellular Telecommunication Networks

Figure 4-17 depicts the techno-economic viable HRES integration to the BTS site stock, as detailed in Table 4-6. The integration of HRES for each BTS site in Bali Province can potentially serve the demand from 10% to 90%, with an average of 57%. The Mac_G_PV HRES generates an average of 66.7 kWh/d, accounting for 81% of the macro BTS site demand. The Mac_R_PV supplies 7.9 kWh/d, or 10% of the demand. The Machub_G_PV (DG) produces 66.8 kWh/d, meeting 50%. The Mic_IBS_R_PV generates 8.3 kWh daily, representing 16%. The Mic_P_PV and Pic_P_PV each generate 12% and 10%.

Figure 4-18 compares energy supply and demand for BTS sites in Bali Province across space occupancy scenarios ranging from 40% to 70%. At 40% occupancy, the system could generate 45 GWh/year, meeting 33% of the 137 GWh annual demand. At 50% and 60% occupancy, potential generation increases to 56 GWh (41%) and 67 GWh (49%), respectively. With 70% site occupancy and economic optimization, the potential generation further increased to 79 GWh/year, supplying up to 57% of the total demand, based on six optimal HRES archetypes identified for the BTS sites in Bali. The aggregated daily energy demand was estimated at 374 MWh/d (15.6 MW), equivalent to 85.4 kWh/d and 3.6 kW per BTS site.

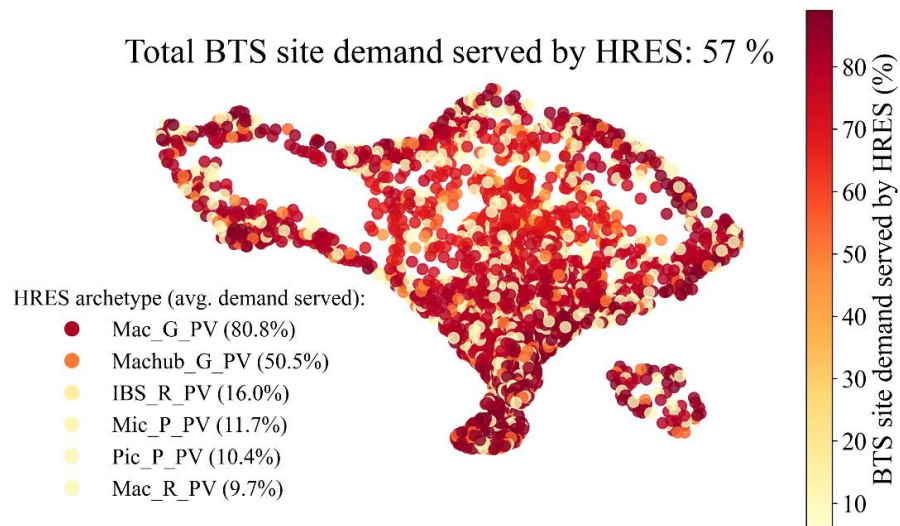


Figure 4-17. Techno-economic viable HRES integration to the BTS site stock in Bali Province.

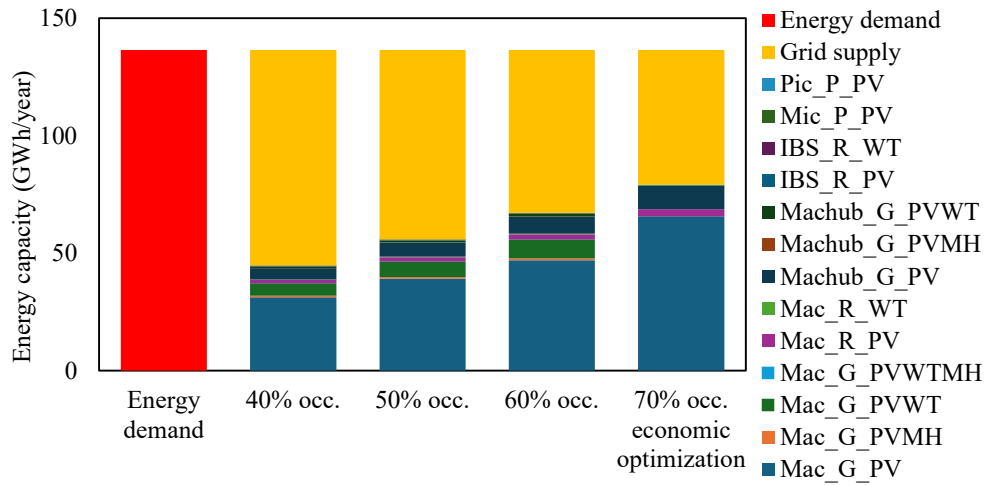


Figure 4-18. Energy supply and demand comparison of BTS site stock in Bali Province.

4.4 Discussion

4.4.1 HRES Integration to the BTS Site

The energy demand from 4,378 BTS site stocks across nine municipalities and five BTS site types in Bali Province were estimated to reach 137 GWh/year or 374 MWh/d. The load estimation of 85.4 kWh/d and 3.6 kW per BTS site reflects the average for all BTS site types in Bali. It closely matches the average load for macro BTS sites (3.4 kW; Table 4-5), which is expected, since macro sites account for about 85% of the total stock as indicated in Figure 4-6. This estimate is consistent with previous studies reporting BTS site energy consumption of 67-466 kWh/day, depending on system configuration [31, 66, 67]. Our earlier work further showed that, when extrapolated nationwide, BTS site stock demand in Indonesia is comparable to the global average, accounting for approximately 2% of national electricity consumption [14, 49].

The integration of HRES reduced the electricity grid purchases by up to 57%, as shown in Figure 4-17, thereby leveraging green energy generation from a combination of renewable resources to meet the demand of BTS sites. Table 4-4 presented 13 HRES archetypes developed based on the site type, deployment type, and suitable renewable energy in Bali Province. The majority of BTS sites are identified to be suitable for solar renewable energy, as indicated by the mapping process (Table 4-3, Figure 4-7(h)). The remaining energy sources included a mix of PV, wind, and hydrokinetic. Energy generation from wind and micro hydrokinetic turbines was lower than anticipated in this study. Nevertheless, if HRES are implemented in regions with greater renewable resource potential, wind and micro hydro turbines may represent a viable option.

Table 4-6. Detail of HRES integration in Bali Province

No	HRES archetype <i>h</i>	Techno-Economic feasibility	Optimum HRES archetypes for Bali province	BTS site stock $NS_{y,m}$	HRES equipment capacity_70% space occupancy (kW)	Avg. daily energy generation (kWh/day)	<i>REstock</i> (MWh/day)
1	Mac_G_PV	yes	Mac_G_PV	2,697	14.28	66.68	179.83
2	Mac_G_PVMH	no					
3	Mac_G_PVWT	no					
4	Mac_G_PVWTMH	no					
5	Mac_R_PV	yes	Mac_R_PV	1,059	1.71	7.97	8.45
6	Mac_R_WT	no					
7	Machub_G_PV (DG)	yes	Machub_G_PV (DG)	405	14.28	66.78	27.04
8	Machub_G_PVMH (DG)	no					
9	Machub_G_PVWT (DG)	no					
10	IBS_R_PV	yes	IBS_R_PV	91	1.71	8.31	0.75
11	IBS_R_WT	no					
12	Mic_P_PV	yes	Mic_P_PV	65	1.02	4.94	0.32
13	Pic_P_PV	yes	Pic_P_PV	61	1.02	4.96	0.30

Of all technically viable HRES archetype combinations, only six HRES configurations (PV-only) are economically feasible (Table 4-6) based on three economic indicators (Figure 4-13). In addition to insufficient renewable energy generation, which increases reliance on the grid, wind and hydrokinetic turbines are substantially more expensive than PV systems. It is important to note that the six viable HRES archetypes are specific to the province of Bali, as the analysis was conducted exclusively with the renewable energy sources available in this region. The HRES performance in Figure 4-13 is broadly comparable to a large-scale HRES deployment across 263 telecom sites in Pakistan, which reported reductions of 34% in NPC and 29% in COE, with a 5-year payback [67]. However, that prior study did not explicitly consider space constraints or heterogeneity within the BTS archetype and focused on off-grid sites, whereas this study includes only on-grid sites.

The total aggregated supply potential from technically and economically viable PV HRES for Bali's BTS site stock is estimated at 79 GWh/year, or 217 MWh/day, assuming 70% site occupancy by PV HRES equipment (Figure 4-10). This maximizes autonomy and minimizes the COE under current site constraints, even with elevated PV structures. Under this deployment scenario, a \$0.10/kWh reduction in grid electricity purchases yields estimated monthly savings of approximately \$650,160. Using a conservative grid emission factor of 0.717 kg CO₂e/kWh [68], the corresponding emission reduction reaches up to 41 kt CO₂e/year. Nevertheless, the remaining energy demand still depends on the conventional power grid, indicating a continued dependence on conventional energy sources.

Grid sales is a common strategy to utilize HRES surplus and reduce costs; however, Indonesian Ministry of Energy and Mineral Resources Regulation No. 2 of 2024 prohibits PV electricity sales [69]. Therefore, grid exports are excluded from this study, and the system is modeled solely on self-

consumption. Figure 4-11 shows that larger battery capacity shifts excess daytime PV to evening demand, reducing grid purchases and improving self-sufficiency, while PV excess reflects insufficient storage. Although higher site occupancy is suitable for larger batteries, even at 70% occupancy, the HRES meets only 57% of total demand, limiting additional applications such as electric vehicle (EV) charging or community needs. Consequently, optimization prioritizes battery sizing to maximize on-site self-consumption rather than grid sales. Net metering provides limited economic benefit due to space-constrained PV capacity and the lack of sustained surplus generation.

The uncertainty of the economic performance, which limits telecom operators from integrating HRES for their cellular networks, is also addressed in this study. The framework identifies viable HRES archetypes prior to large-scale integration, which vary by the region based on the local geographical and renewable energy potential. The current 0.1 \$/kWh grid tariffs in Indonesia hinder telecom operators' ability to integrate HRES, especially at on-grid sites, thereby slowing adoption. As shown in Figure 4-16, returns on investment occur only after 8–9 years. Due to high upfront costs, operators are unlikely to adopt HRES without strong government policy support. Reforming electricity subsidies to reduce capital costs of HRES could incentivize adoption. This policy dilemma is a key issue for future research.

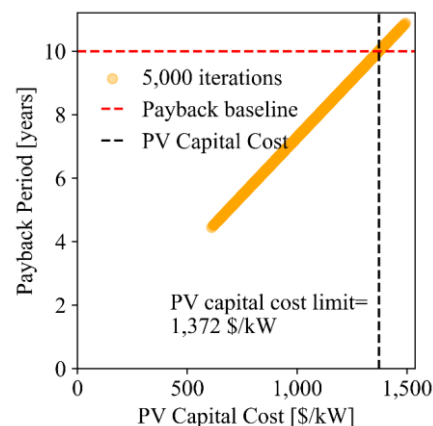


Figure 4-19. PV capital cost effects to payback period.

Figure 4-19 extends the economic assessment of the Mac_G_PV HRES, indicating that PV capital costs must not exceed \$1,372/kW to maintain a payback period below 10 years. If costs are reduced to \$600/kW, the payback period decreases to approximately 4 years, making the HRES integration more attractive. To reflect market variability in Indonesia—driven by logistics, transportation, island fragmentation, and limited vendor competition—PV capital cost was modeled using a triangular distribution (min: \$600/kW; mode: \$1,100/kW; max: \$1,500/kW), while assuming all other parameters remain constant. A 5,000-iteration Monte Carlo simulation, assuming linear scaling from the base cost of \$1,100/kW, was conducted to evaluate how uncertainty affects payback

period for large-scale HRES deployment. Additionally, the balance between the demand and supply of HRES can be evaluated (Figure 4-11) to assess the energy efficiency of the BTS site (Figure 4-18), thereby providing cost savings for the telecom operator.

4.4.2 HRES Framework

The case study demonstrates that the proposed framework-based model meets the requirements outlined in literature review section and advances the state of the art established by previous research. Extending the macro-level energy demand model analysis for BTS site stock [14], the HRES framework offers additional contributions through the following analyses:

1. Mapping of synthetic BTS site stock and renewable energy resources.
2. Identification of hybrid renewable energy system archetypes.
3. Assessment of techno-economic performance at the stock level.

The synthetic BTS site stock was used to assign attributes (such as location, type, and renewable potential) based on spatial and statistical models from sample sites reflecting the real network. It enables refinement from municipal-level spatial resolution, which is used to quantify the BTS site stock composition for demand modeling, to a more detailed site-level analysis. The synthetic BTS site distribution (Figure 4-7(d)) is derived from the actual BTS samples representing the cellular network. Obtaining precise coordinates for all the BTS sites is nearly impossible owing to confidentiality, making it essential to create a synthetic spatial distribution. This satisfies the requirement to enhance the framework scalability analysis of the energy supply and demand balance at the BTS site when integrating renewable energy.

Validation for synthetic BTS sites is conducted by comparing density distributions to determine whether the synthetic kernel density raster spatially aligns with the sample density raster. Appendix E shows eight of nine municipalities exhibit mean differences below 0.05 (5%), indicating good spatial agreement and no systematic bias; Denpasar shows the largest difference but remains within the acceptable $\pm 15\%$ range. Standard deviations are below 3% in five municipalities, and the rest are under 12%, indicating overall spatial consistency between the synthetic and sample density surfaces.

Each synthetic point is assigned characteristics of the BTS site archetypes (Appendix A), including the types, deployment, and power consumption. The synthetic BTS sites are then mapped with renewable energy sources (Figure 4-7 e, f, g) to develop an HRES archetype (Table 4-4). Satisfying the requirement to evaluate the HRES archetype design involves considering the geographical constraints, BTS sites characteristics, site dimensions, and space availability by representing all the sites with similar characteristics.

The deployment area specification of the BTS site adheres to the relevant standards for telecom tower construction, including both the international guidelines and local government regulations (Table 4-1). The BTS site area for the greenfield deployment is 100 m², as presented in Table 4-4,

which meets the guideline 81 m² minimum for 30 m tower height. This finding supports the validity of the online survey results within the HRES development process.

Existing battery capacity (Appendix B) and calculated requirement comparison (Table 4-5) situation reflect both demand- and deployment constraint-driven design considerations. IBS and pico sites are typically deployed in high-traffic environments, such as shopping centers and office buildings, where priority customer profiles require enhanced backup. Moreover, permitting requirements and limited site accessibility necessitate larger battery capacities to ensure reliable operation during outages or troubleshooting, constraints that are less relevant for other site types.

The framework is applicable to other regions by adjusting the modeling component. Starts with defining BTS site archetypes and regional stock composition [14], established using BTS site samples or, if unavailable, by applying Appendix A. Potential 5G deployments may be incorporated at this stage, depending on sample availability. The BTS site stock model examines the relationship between the composition of BTS site samples and socioeconomic factors (e.g., population density). The official total BTS site count for the region is then adjusted to reflect the examined composition. As complete spatial BTS site samples are typically unavailable, a synthetic BTS site stock spatial distribution model, is necessary to ensure realistic renewable energy mapping and robust HRES archetype development. Regional geographic and meteorological data are required, with renewable energy capacity installed based on available space at each HRES archetype. Moreover, Techno-economic parameters should be tailored to local conditions, enabling the model's applicability beyond the sampled regions.

4.4.3 Limitations and Future Work

The proposed framework did not consider annual changes in the BTS site deployment, techno-economic parameters, or the cost reductions associated with bulk purchases of HRES equipment. Future work must address the resilience of the BTS site during extreme outages, improve calculation resolution, optimize spatial allocation, and account for annual changes in techno-economic parameters. This includes an environmental assessment and cross-regional validation of HRES implementation. Further analysis of policy aspects is also necessary. As previously mentioned, expanding electricity subsidies to telecommunication stakeholders could reduce the capital costs of HRES and incentivize large-scale adoption.

4.5 Conclusion

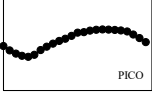
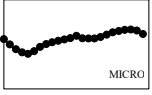
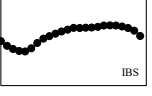
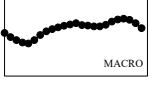
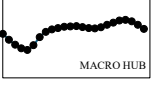
This study presents a scalable framework analysis of the hybrid renewable energy system integration into cellular telecommunication networks. The proposed framework illustrates the actual cellular telecommunications network by creating a synthetic BTS site stock spatial distribution and mapping it with renewable energy potential. Each BTS site is embedded with the site profile information, including its energy demand, battery capacity, and site space availability to develop the HRES archetype. The spatiotemporal decomposition features of the energy demand model reported in

previous studies ensure the scalability of the HRES analysis. The result demonstrated that the proposed framework fulfilled the following requirements for comprehensive HRES analysis: 1) scalability for evaluating the energy supply and demand balance of BTS sites, 2) ensure comprehensive alignment of the regional renewable energy potential, geographical conditions, and site space availability when developing HRES archetypes, and 3) techno-economic assessment to identify the viable HRES archetypes before integration.

Based on a case study in Bali, Indonesia, the framework identified only six out of the 13 HRES archetypes with techno-economic viability, all of which had solar PV potential. Integrating the PV HRES into a cellular telecommunication network with 70% site occupancy could generate 79 GWh/year, meeting 57% of the annual demand of 137 GWh. This study presented a reference method for synthesizing the spatial distribution of the BTS site stock and assigning attributes of the archetype characteristics to each BTS site, ensuring a precise representation of the cellular telecommunication networks. By integrating the renewable energy sources, HRES archetypes were developed and their effectiveness in satisfying the energy demands of these networks, which can be scaled to the national level, were evaluated. This findings indicate that energy efficiency improvement and energy cost reduction can be simultaneously achieved in the growing telecom industry, contributing to the energy transition target of the Indonesia government.

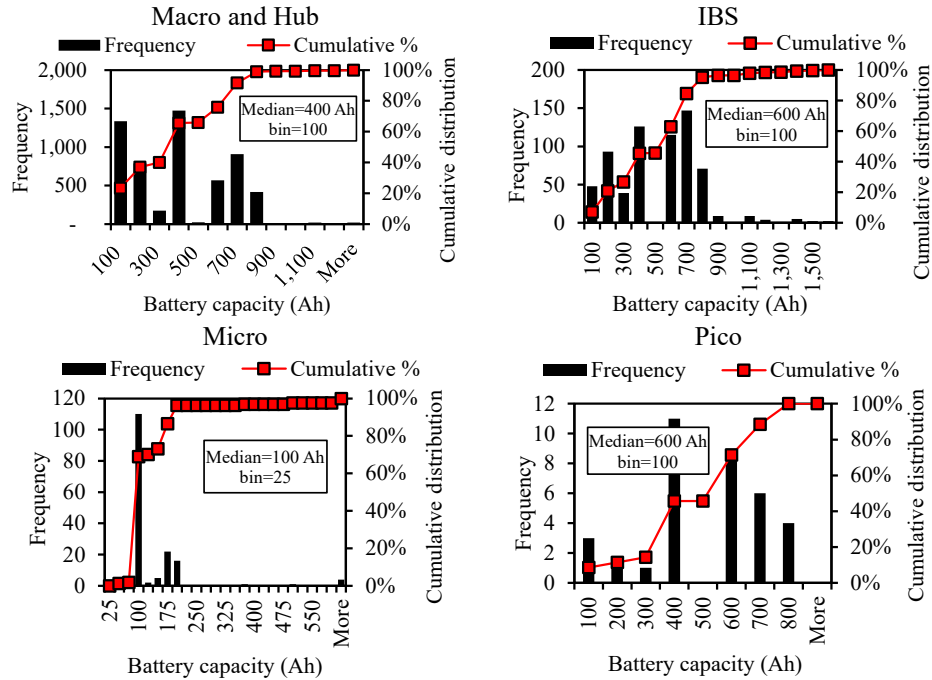
4.6 Appendix

4.6.1 Appendix A. BTS Site Archetype Characteristics [14]

Archetype	Site type y	$P_{peak,y}$ (kW)	Power factor $PF_{y,t}$	Daily energy demand $PC_{y,t}$ (kWh/d)	Equipment cabinet	Antenna Height (m)	Deployment	Avg. site area (m ²)	Physical appearance $physic_y$
Type 1	Pico	2.4		47.7	Mounted	2–5	Retail, shopping area, Roadside unit (RSU)	2–5 (max for pole)	
Type 2	Micro	2.1		42.4	Mounted	5–10	RSU, building facade, Grid pole	2–5 (max for pole)	
Type 3	IBS	2.5		51.9	Indoor	3–5 (ceiling)	In-building system with DAS	50*	
Type 4	Macro	4.2		82.6	Outdoor	20–35	Greenfield or rooftop (outdoor)	50–130	
Type 5	Macro hub	6.7		132.1	Indoor	35–50	Greenfield (shelter) + air conditioner	130	

*assumed as a maximum spatial leasing on the building roof

4.6.2 Appendix B. Existing Battery Capacity for Each BTS Site



4.6.3 Appendix C. Techno-economic Assessment Parameters

No	Component	Parameter	Value	Unit	References
1	Battery	Autonomy	6	hour	SAIDI Indonesia
		DoD	80	%	[70]
		η_{batt}	98	%	[70]
		V_{sys}	48	VDC	BTS equipment voltage
		$Batt_{deg}$	20	%	[62]
		Battery capital cost	78	\$/kWh	[71]
		Battery replacement cost	40	\$/kWh	Estimation from past trend [70]
		Battery O&M cost	1	\$/kWh/year	estimation
2	Diesel generator (DG)	smf	1.25		[72]
		DG capital cost	1	\$/kW	existing DG
		DG replacement cost	500	\$/kW	[72]
		DG O&M cost	0.03	\$/op.hr	estimation
		DG lifetime	15,000	hours	[72]
		Fuel price	1.3	\$/L	[73]
3	Solar photovoltaic (PV)	η_{pv}	20.4	%	SunPower E series: E20-327 [74]
		η_{sys}	90	%	[32]
		GHI	3 – 6	kW/m ² /d	[52]
		A_{pv}	5 - 70	m ²	BTS site 70% space occupation
		PV derating power	88	(%)	[74]
		PV capital cost	1,100	\$/kW	Actual implementation sample, IRENA [75]
		PV replacement cost	0	\$/kW	No replacement needed
		PV O&M cost	10	\$/kW//year	Estimation
4	Grid	PV module lifetime	25	years	[74]
		Electricity price	0.1	\$/kWh	[76]
5	Wind turbine (WT)	ρ_{wind}	1.225	kg/m ³	[58]
		$A_{WTrotor}$	3.2	m ²	Aeolos 1kW Vertical WT [59]
		$CP_{turbine}$	0.5		[58]
		V_{wind}	3 - 9	m/s	[53]
		WT capital cost	5,320	\$/kW	[59]
		WT replacement cost	0	\$/kW	No replacement needed
		WT O&M	10	\$/kWh/year	Estimation
		WT lifetime	25		Estimation
6	Micro hydrokinetic	ρ_{hydro}	1,000	kg/m ³	[60]
		$A_{MHrotor}$	1	m ²	[61]
		$CP_{turbine}$	0.5		[60]
		V_{stream}	0.4 - 1	m/s	[54]
		MH capital cost	14,000	\$/kW	[61]
		MH replacement cost	10,000	\$/kW	estimation
		MH O&M cost	100	\$/kWh/year	estimation
		MH lifetime	10		estimation
7	Converter	Converter capital cost	300	\$/kW	HOMER [64]
		Converter replac. cost	300	\$/kW	HOMER [64]
		Converter O&M cost	0	\$/kWh/year	HOMER [64]
		Converter lifetime	15	years	HOMER [64]
		Efficiency	95	%	HOMER [64]
8	Economic	Nominal disc. rate i'	8	%	[77]
		Inflation rate f	3.71	%	[77]
		R_{proj}	25	years	
		Exchange rate	16,500	IDR/1USD	

4.6.4 Appendix D. Economic Performance Indicator

Net Present Cost (NPC)

The total NPC represents the life-cycle cost of the system by condensing all the expenditures and revenues into a single value using a defined discount rate. It considers the construction, replacements, maintenance, fuel, grid purchases, and emission penalties, whereas the revenues include power sales and salvage value, as expressed below:

$$NPC = \frac{C_{ann,tot}}{CRF(i, R_{proj})} \quad 4-6$$

where $C_{ann,tot}$ denotes the total annualized cost of electricity production (4-7), CRF denotes the capital recovery factor (4-8), i denotes the annual real discounted rate (4-9), and R_{proj} denotes the project lifetime. The annual real discounted rate, i , considers the nominal discounted rate, i' , and expected inflation rate, f , as inputs.

$$C_{ann,tot} = CRF(i, R_{proj}) \cdot NPC \quad 4-7$$

$$CRF(i, R_{proj}) = \frac{i(1+i)^{R_{proj}}}{(1+i)^{R_{proj}} - 1} \quad 4-8$$

$$i = \frac{i' - f}{1 + f} \quad 4-9$$

Cost of Energy (COE)

COE represents the average cost per kWh of useful electrical energy produced by a system. It is calculated by dividing the total annualized cost of electricity production $C_{ann,tot}$ by the total amount of useful electrical energy produced by the system, as expressed in (4-10). $E_{served,AC}$ and $E_{served,DC}$ denote the electrical AC and DC loads that the system provides per year, respectively, and $E_{seles,grid}$ denotes the amount of energy sold to the grid per year.

$$COE = \frac{C_{ann,tot}}{E_{served,AC} + E_{served,DC} + E_{sales,grid}} \quad 4-10$$

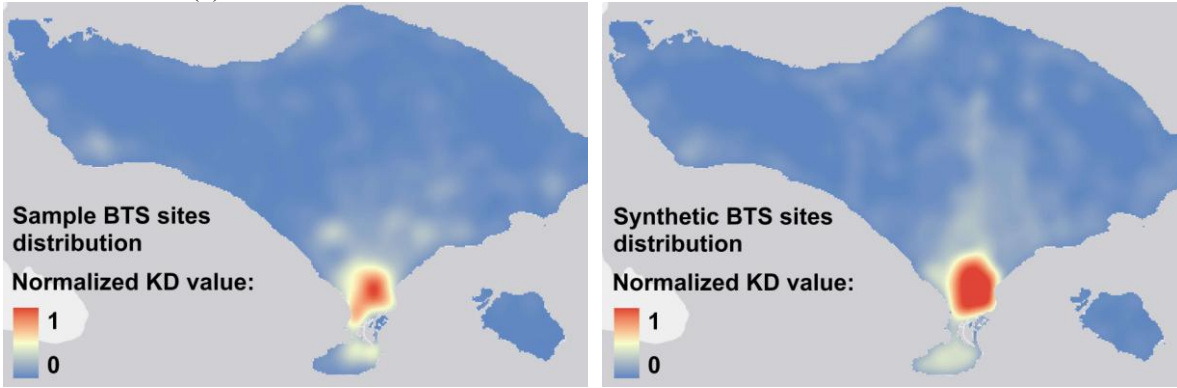
Payback period (Payback)

Payback is the time required for investors to recover their initial investment, $Investment_{initial}$. It serves as a metric for evaluating the risk of renewable energy projects and helps rank those that offer early financial returns. The initial investment is divided by the net change of cumulative cash inflow, CCF_{in} , and cumulative cash outflow, CCF_{out} , as expressed below.

$$Payback = \frac{Investment_{initial}}{CCF_{in} - CCF_{out}} \quad 4-11$$

4.6.5 Appendix E. Synthetic BTS site distribution validation against actual BTS site implementation

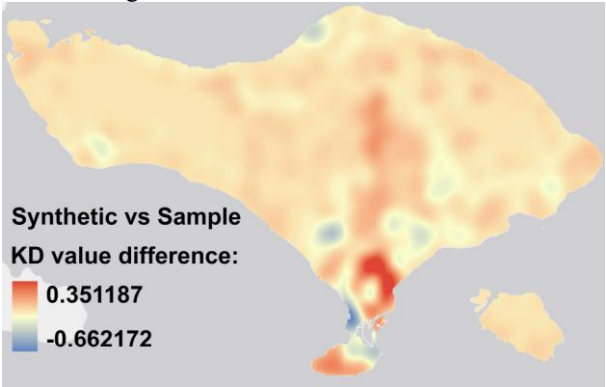
- a. Create the normalized kernel density pixel map (raster) of the samples (a) and the synthetic distribution (b)



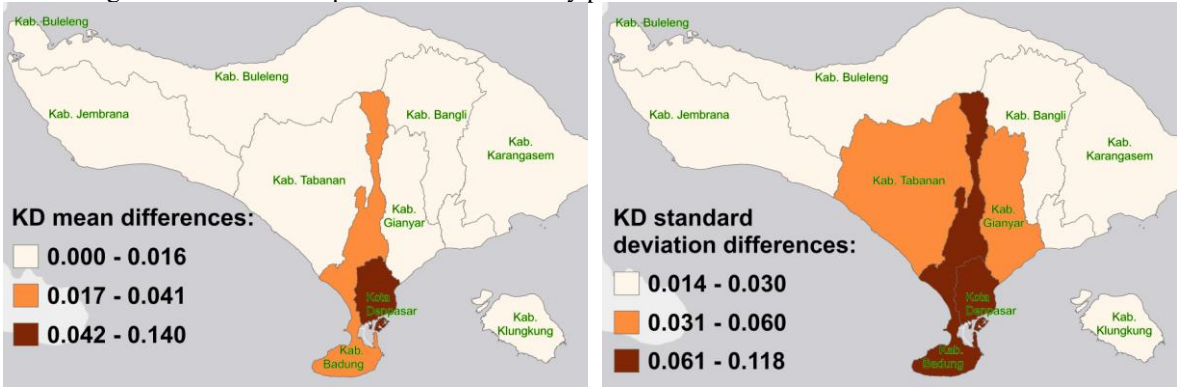
(a)

(b)

- b. Subtraction kernel density raster comparing the sample and synthetic distributions. Positive values indicate overestimation, while negative values indicate underestimation.



- c. Zonal (municipal level) statistics of the subtraction raster: (a) Mean (b) Standard deviation. Classified using Jenks method to explore the actual density pattern.



(a)

(b)

5 Integrated Discussion

This chapter provides a comprehensive discussion of the study's key findings in relation to the research objectives, outlines the main contributions, and examines the limitations and uncertainties of the developed framework.

5.1 Foundation Methodology of Energy Demand Model for Cellular Telecommunication

Networks

Telecom operators can estimate their total energy demand by reviewing their monthly electricity bills. However, this process requires significant effort, as they need to gather data from the sub-district level to the national level. In the case of Indonesia, the focus of this research, telecom operators report only the total annual energy demand for their cellular networks, lacking detailed information about the local characteristics of BTS site stock. Furthermore, this data is confidential and not sublicensed, making it challenging to estimate national energy demand across multiple telecommunications operators accurately. During research visits to Indonesia's Ministry of Communication and Digital Affairs in 2024, we discovered that the government lacks data on national energy demand for cellular telecommunications networks. As an initial methodological foundation for developing the energy demand model for telecommunication networks, we adopted a method commonly used to calculate the energy demand of a building stock. This was not only because a telecom site is comparable to a "building" but also because the building sector is more mature and advanced in research on energy system efficiency and emission reduction.

Chapter 2 provides a detailed explanation of the established four steps of the macro-level BTS stock energy demand model: segmentation, characterization, quantification, and aggregation. As discussed more thoroughly in Section 2.4, during the segmentation process, we found that the type, system configuration, and proportion of the BTS strongly influence the energy demand calculation for the BTS network at the macro level. The density category of the region also affects the respective proportion of the BTS segments according to the population. BTS archetypes are developed in the characterization step of the model based on the statistical test results, along with the physical and technical characteristics of each BTS segment. Moreover, the daily peak/off-peak hours of data traffic and the BTS's power consumption characteristics for each density category are also identified. Hourly power consumption for each BTS segment is calculated during the quantification steps and then scaled by the number of BTS stock in the region (municipality level). The results from each region are then aggregated to determine the total energy demand at the regional level. However, our model indicates that energy demand from cellular telecommunication networks represents 4.6% of total national electricity consumption. This figure is higher than observed in European countries and Japan, where energy demand from telecommunication networks accounts for less than 3% of total national consumption.

5.2 Macro-Level Energy Demand Model for Cellular Telecommunication Networks

Applicability Across Regions

With the foundational method established, the second stage of this research focuses on improving the model's accuracy, reliability, and applicability to regions with similar characteristics. This refinement is essential given the model's tendency to overestimate energy demand. To address this, we enhance data resolution and validity through a research visit to Indonesia. During this visit, we conducted data verification with key stakeholders in the national telecommunications ecosystem—including the Ministry of Communication and Digital Affairs, three telecom operators in Indonesia, an equipment vendor, a utility company, and a contractor—and collected additional data through an on-site survey. The most important takeaway from the research visit is the clarification provided by telecom operators concerning the BTS Network Elements (NE) and BTS sites. In Indonesia, the number of BTS NEs is widely available, as major telecom operators disclose this information. However, information on energy consumption for these elements is lacking, as energy consumption is measured at the BTS site level. A single BTS site may integrate multiple NEs, making it challenging to attribute energy usage directly to individual elements. Therefore, the proposed framework will utilize BTS sites as the modeling unit, rather than BTS NEs, as was done in the initial stage. In addition, we successfully acquired BTS log data from 40 BTS sites, a significant increase from the four sites examined in the prior study. The selection of these sites was based on criteria such as site type, regional density category, and NE configuration. Furthermore, we conducted an on-site survey to validate the physical characteristics of each BTS site.

Chapter 3 outlines in detail how the enhanced macro-level energy demand model for Indonesia's cellular telecommunications networks reduces overestimation and ensures applicability across regions. As discussed more thoroughly in Section 3.4, Indonesia's average total energy demand from the BTS site stock was 14.7 GWh/day, or 613.5 MW. Equivalent to 84.7 kWh/day and 3.5 kW per BTS site, based on a total of 173,886 BTS sites in Indonesia. Annual electricity consumption was estimated at 5.37 TWh/year (613.5 MW on average), equivalent to 1.96% of national electricity use—closely aligning with the global average of around 2%. This estimate is 58% lower than that derived from the initial method, primarily because the earlier study did not consider spatial variation in BTS site stock or use individual BTS sites as the modeling unit.

Using the BTS site as the modeling unit and applying the Dirichlet regression model addressed the limitation of the site-level dataset. Although it was sufficiently large to capture BTS site characteristics, it was not representative of the national BTS stock. By incorporating socioeconomic factors into the estimation of site stock composition for each municipality, the model reduced the potential for errors arising from extrapolating from a non-representative sample to a country with significant regional development disparities. The Dirichlet regression model effectively represented Indonesian municipalities, encompassing a diverse range of rural and urban municipalities.

Furthermore, we selected widely available socioeconomic variables as predictors, enabling the model to demonstrate the relationship between municipal population density and the proportion of BTS sites. The framework can be adapted to other regions by adjusting each modeling component. BTS archetypes may be derived from local samples, or, in the absence of data, by utilizing generalized characteristics identified in this study. The physical and technical attributes used here are relevant to countries with similar network characteristics. BTS site stock can be modeled directly when data are available or estimated using regression approaches in combination with a Dirichlet regression model. Overall, the analysis demonstrates that BTS stock composition can be inferred from widely accessible indicators such as population density, enabling the model's broader applicability; higher population density generally corresponds to denser BTS deployment.

5.3 Assessment of HRES Integration into Cellular Telecommunication Networks

Following the estimation of cellular network energy demand, the final research objective was to assess the feasibility of integrating renewable energy to meet this demand. The integration framework combines the synthetic BTS stock with BTS archetypes to evaluate HRES design and operation, ensuring compatibility with diverse BTS site types, existing electrification systems, and renewable energy constraints. A synthetic spatial distribution represents the regional BTS stock at the macro level, with the total number and composition determined by a statistical model reflecting socioeconomic conditions. Each synthetic BTS site is assigned a random location within the study area, allowing renewable energy resources to be allocated according to local geographical and meteorological conditions. Power consumption and characteristics of the BTS site archetype are assigned to each synthetic BTS site, along with renewable energy data, to develop HRES archetypes. The spatial constraints, including site dimensions and space occupation for each archetype, are derived from surveyed BTS samples to support equipment selection and capacity assessment.

Various BTS site types integrated with HRES were evaluated together with existing energy supply options—battery, diesel generator, and grid—to balance energy demand and battery charging requirements. The energy generation potential of each HRES was calculated, and the battery and DG capacities were validated to ensure compliance with minimum backup and storage requirements. Viable HRES configurations were then identified through an economic assessment, in which sensitive parameters were optimized, and the resulting economic indicators were compared against those of the baseline BTS configuration. Additionally, the influence of varying sensitive parameters on economic performance was evaluated. The techno-economic viability of the HRES configuration was then simulated across the regional BTS site stock. Lastly, the performance of HRES stock, along with CO₂ reduction and cost savings, was measured. This method supports site-level evaluations that can be scaled nationally, enhancing BTS site energy efficiency on a larger scale.

Chapter 4 provides a detailed assessment of the integration of HRES into cellular telecommunication networks. As discussed more thoroughly in Section 4.4, the energy demand from

4,378 BTS site stocks across nine municipalities and five BTS site types in Bali Province was estimated at 137 GWh/year, or 374 MWh/d (15.6 MW), equivalent to 85.4 kWh/d and 3.6 kW per BTS site. The total potential for aggregated supply generation of HRES, assuming a 70% site occupancy scenario at BTS, was calculated to be 79 GWh/year or 217 MWh/day, which meets 57% of the total energy demand. The synthetic BTS site stock and renewable energy mapping indicates that 84.4% of BTS sites are compatible with solar PV energy. The remaining sites have a combination of solar, wind, and hydrokinetic resources. These three renewable energy sources are identified as having the highest potential by the Ministry of Energy and Mineral Resources of Indonesia.

By applying BTS site archetype characteristics to the synthetic BTS stock, the study developed 13 HRES archetypes. However, not all were economically viable, as wind and hydrokinetic generation in Bali Province was lower than anticipated and substantially more costly than PV systems. The NPC and COE of the viable HRES were 5% to 28% lower than the baseline, with a payback period of 3 to 9 years, depending on the deployment size. The HRES achieves monthly cost savings of approximately \$650,160 by reducing electricity purchases at \$0.10/kWh. Using a conservative emission factor of 0.717 kg CO₂e/kWh for Indonesia's grid, CO₂ emissions are reduced by up to 41 kt CO₂e/year. Nevertheless, the remaining energy demand continues to rely on the conventional grid, indicating ongoing dependence on traditional energy sources.

5.4 Future Works and Limitations

The developed framework demonstrates promising results and practical relevance. However, it is essential to acknowledge its existing limitations, which are detailed as follows:

1. The Indonesian telecom operator had dismantled all 3G equipment, with only a few 2G and 5G systems in the transition phase. Because of the dominant proportion and extensive data availability, we considered only 4G BTS networks in this study. Therefore, it may not be applicable to countries that have already transitioned to 5G.
2. The proposed method does not consider telecom network elements other than those of BTS, including mobile switching, core transmission, data center, and retail office.
3. Our model did not consider the annual changes in BTS site deployment. The projected annual growth rate of 20% until 2029 makes evaluating the future energy demand critical.
4. Seasonal variation in Macro Hub air-conditioner power consumption may be underestimated, as *btslog* data were available for only four months.
5. The model does not account for potential cost reductions from bulk purchases of HRES equipment.

Therefore, future works are required to improve the framework's reliability and extend the contribution as follows:

1. Thoroughly evaluate the uncertainty of input parameters in future energy demand calculations, including spatio-temporal modeling of BTS site development and projections.

2. Incorporate air-conditioning units into BTS site archetypes to evaluate how meteorological conditions and operator strategies—such as scheduling, temperature adjustments, and passive cooling—impact overall energy demand. This will involve collecting annual BTS logs along with meteorological data to account for seasonal variability.
3. Investigate alternative compositional regression methods in addition to the Dirichlet regression model for estimating BTS site stock composition.
4. Assess the resilience of BTS sites during extreme outages, including the associated costs of diesel generators (DGs) and fuel for the Machub_G_PV systems, and conduct an environmental impact analysis.
5. Address not only the technical aspects of HRES but also the economic and policy dimensions to accelerate the clean energy transition and support sustainable implementation.

6 Conclusion

This dissertation aims to develop reliable energy demand methods for cellular telecommunications networks and evaluate the techno-economic feasibility of integrating these models with renewable energy resources. Focusing on Indonesia's cellular telecommunications networks, particularly in Bali Province, this study emphasizes the framework's applicability and scalability at the macro level. It utilizes parameters that can serve as a reference for all regions, especially in data-limited areas such as developing Asian countries. Moreover, this study addresses the absence of a comprehensive framework that captures BTS site stock composition, spatial distribution, and the physical and technical characteristics that shape energy-demand behavior. It advances macro-level HRES implementation analysis by developing a scalable framework for integrating HRES generation supply with the energy demands of BTS site networks, from the individual site level to the national scale.

Chapter 2 established the foundational four steps of the macro-level BTS stock energy demand model: segmentation, characterization, quantification, and aggregation, adopting concepts commonly employed in the building sector. The segmentation showed that BTS type, system configuration, and segment proportions significantly influence macro-level energy demand, while regional density shapes the distribution of BTS segments relative to population. In the characterization step, we developed BTS archetypes based on statistical test results and the physical and technical characteristics of each segment. We also identified the daily peak and off-peak hours of data traffic and the power consumption characteristics of the BTS for each density category. Hourly power consumption for each BTS segment is quantified and scaled according to the number of BTS sites in each municipality during the quantification process. Regional totals are then aggregated to estimate the overall energy demand. Our model shows that energy demand from cellular telecommunication networks is 4.6% of total national electricity consumption, higher than in European countries and Japan, where it is under 3%.

Chapter 3 outlined an enhanced macro-level energy demand model for cellular networks that supports scalability at the stock level, incorporates the BTS site stock composition and characteristics to reduce overestimation, and ensures applicability across regions. Data resolution and validity were enhanced through a research visit to Indonesia, which included verification with representatives from national telecom stakeholders and on-site surveys. The model estimated Indonesia's total daily energy demand for the BTS site stock to be 14.7 GWh/day, or 613.5 MW. Averaging to 84.7 kWh/day and 3.5 kW per BTS site, based on a total of 173,886 BTS sites in Indonesia. This represented an annual requirement of 5.37 TWh, accounting for 1.96% of the country's total electricity consumption in 2022. The model enhancement reduced overestimation by up to 58%, primarily because the earlier study did not account for spatial variation in BTS site stock or use individual BTS sites as the modeling unit. The model integrated stock composition with the representation of BTS sites, demonstrating the spatiotemporal decomposition of energy demand. Herein, the representation of a BTS site through

archetype development is relevant to similar regional contexts, particularly neighboring Asian countries. Furthermore, our model used universally accessible predictors, such as population density, in the BTS site composition analysis, ensuring its applicability to other regions, even those with limited available data.

Chapter 4 presented a reference method for synthesizing the spatial distribution of the BTS site stock and assigning archetype characteristics to each site, ensuring an accurate representation of the cellular network. The chapter focused on assessing the integration of HRES to meet the energy demand of cellular telecommunication networks. A total of 4,378 synthetic spatial distributions of BTS site stocks and their composition, determined by a statistical model reflecting socioeconomic conditions, represented the BTS stock at the macro level across Bali Province. Each synthetic BTS site is assigned a random location within the study area, allowing renewable energy resources to be allocated according to local geographical and meteorological conditions. Power consumption and characteristics of the BTS site archetype are assigned to each synthetic BTS site, along with renewable energy data, to develop HRES archetypes. The spatial constraints, including site dimensions and space occupation for each archetype, are derived from surveyed BTS samples to support equipment selection and capacity assessment. The framework identified only six out of the 13 HRES archetypes with techno-economic viability, all of which had solar PV potential. The NPC and COE of the viable HRES were 5% to 28% lower than the existing electrification, with a payback period of 3 to 9 years, depending on the deployment size. Integrating the PV HRES into a cellular telecommunication network with 70% site occupancy could generate 79 GWh/year, meeting 57% of the annual demand of 137 GWh. The result demonstrated that the proposed framework fulfilled the following requirements for comprehensive HRES analysis: 1) scalability for evaluating the energy supply and demand balance of BTS sites, 2) ensure comprehensive alignment of the regional renewable energy potential, geographical conditions, and site space availability when developing HRES archetypes, and 3) techno-economic assessment to identify the viable HRES archetypes before integration.

Overall, this dissertation has introduced a macro-level energy demand modeling framework for cellular telecommunication networks that addresses the limitations of conventional approaches. This has enhanced the understanding of the composition of the BTS site stock in Indonesia, including its spatial distribution and energy demand characteristics, offering valuable insights for developing regions, particularly in Asia. Furthermore, this dissertation presented a scalable framework for implementing HRES within cellular telecommunications networks while ensuring economic feasibility, demonstrating both the energy-generating potential of HRES and its effectiveness in meeting cellular network demands. Finally, from a practical perspective, this dissertation provided telecom operators with a reference for integrating HRES into their networks to enhance overall revenue through improved energy efficiency and reduced energy costs, while supporting national green energy transition goals.

References

- [1] “Ericsson Mobility Report June 2019.” Accessed: Nov. 10, 2025. [Online]. Available: <https://www.ericsson.com/en/mobilityreport/reports/june-2019/mobile-subscriptions-q1-2019>
- [2] M. H. Alsharif, A. H. Kelechi, J. Kim, and J. H. Kim, “Energy Efficiency and Coverage Trade-Off in 5G for Eco-Friendly and Sustainable Cellular Networks,” *Symmetry*, vol. 11, no. 3, p. 408, Mar. 2019, doi: 10.3390/sym11030408.
- [3] “Latest data and forecasts – Ericsson Mobility Report,” ericsson.com. Accessed: Nov. 12, 2025. [Online]. Available: <https://www.ericsson.com/en/reports-and-papers/mobility-report/dataforecasts>
- [4] “Telecom, ICT and Energy,” Sofrecom. Accessed: Nov. 25, 2025. [Online]. Available: <https://www.sofrecom.com/en/news-insights/telecom-ict-and-energy.html>
- [5] M. H. Alsharif, J. Kim, and J. H. Kim, “Green and Sustainable Cellular Base Stations: An Overview and Future Research Directions,” *Energies*, vol. 10, no. 5, p. 587, May 2017, doi: 10.3390/en10050587.
- [6] G. Bonire and A. Gbenga-Ilori, “Towards artificial intelligence-based reduction of greenhouse gas emissions in the telecommunications industry,” *Sci. Afr.*, vol. 12, p. e00823, Jul. 2021, doi: 10.1016/j.sciaf.2021.e00823.
- [7] A. Jahid, A. B. Shams, and Md. F. Hossain, “Green energy driven cellular networks with JT CoMP technique,” *Phys. Commun.*, vol. 28, pp. 58–68, Jun. 2018, doi: 10.1016/j.phycom.2018.03.008.
- [8] “The key to lowering telecom costs: Energy | McKinsey.” Accessed: Nov. 25, 2025. [Online]. Available: <https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/the-case-for-committing-to-greener-telecom-networks>
- [9] N. R. Deevela, T. C. Kandpal, and B. Singh, “A review of renewable energy based power supply options for telecom towers,” *Environ. Dev. Sustain.*, vol. 26, no. 2, pp. 2897–2964, Feb. 2024, doi: 10.1007/s10668-023-02917-7.
- [10] R. Kaur, V. Krishnasamy, N. K. Kandasamy, and S. Kumar, “Discrete Multiobjective Grey Wolf Algorithm Based Optimal Sizing and Sensitivity Analysis of PV-Wind-Battery System for Rural Telecom Towers,” *IEEE Syst. J.*, vol. 14, no. 1, pp. 729–737, Mar. 2020, doi: 10.1109/JSYST.2019.2912899.

- [11] D. Wilson, “When can we afford to deploy solar for on-grid solutions in telecom?,” in *2017 IEEE International Telecommunications Energy Conference (INTELEC)*, Oct. 2017, pp. 8–15. doi: 10.1109/INTLEC.2017.8211669.
- [12] “Mobile Net Zero: State of the Industry on Climate Action 2022,” External Affairs. Accessed: Nov. 25, 2025. [Online]. Available: https://www.gsma.com/solutions-and-impact/connectivity-for-good/external-affairs/gsma_resources/mobile-net-zero-state-of-the-industry-on-climate-action-2022-report/
- [13] “Permen ESDM No. 10 Tahun 2025,” Database Peraturan | JDIH BPK. Accessed: Aug. 31, 2025. [Online]. Available: <http://peraturan.bpk.go.id/Details/317729/permen-esdm-no-10-tahun-2025>
- [14] M. M. M. Dinata, Y. Yamaguchi, H. Uchida, Y. Shimoda, and A. Subekti, “Macro-Level Energy Demand Model for Cellular Telecommunication Networks,” *IEEE Access*, vol. 13, pp. 144982–144994, 2025, doi: 10.1109/ACCESS.2025.3599587.
- [15] “Latest data and forecasts – Ericsson Mobility Report.” Accessed: Nov. 25, 2025. [Online]. Available: <https://www.ericsson.com/en/reports-and-papers/mobility-report/dataforecasts>
- [16] M. Etoh, T. Ohya, and Y. Nakayama, “Energy Consumption Issues on Mobile Network Systems,” in *2008 International Symposium on Applications and the Internet*, Jul. 2008, pp. 365–368. doi: 10.1109/SAINT.2008.84.
- [17] W. Van Heddeghem, S. Lambert, B. Lannoo, D. Colle, M. Pickavet, and P. Demeester, “Trends in worldwide ICT electricity consumption from 2007 to 2012,” *Comput. Commun.*, vol. 50, pp. 64–76, Sep. 2014, doi: 10.1016/j.comcom.2014.02.008.
- [18] D. Lundén, J. Malmmodin, P. Bergmark, and N. Lövehagen, “Electricity Consumption and Operational Carbon Emissions of European Telecom Network Operators,” *Sustainability*, vol. 14, no. 5, Art. no. 5, Jan. 2022, doi: 10.3390/su14052637.
- [19] “New Site Power Consumption Assessment: Ericsson equipment.” Ericsson, Unpublished.
- [20] M. Deruyck, W. Joseph, and L. Martens, “Power consumption model for macrocell and microcell base stations,” *Trans. Emerg. Telecommun. Technol.*, vol. 25, no. 3, pp. 320–333, 2014, doi: 10.1002/ett.2565.
- [21] C. A. Chan, A. F. Gygax, E. Wong, C. A. Leckie, A. Nirmalathas, and D. C. Kilper, “Methodologies for Assessing the Use-Phase Power Consumption and Greenhouse Gas Emissions of Telecommunications Network Services,” *Environ. Sci. Technol.*, vol. 47, no. 1, pp. 485–492, Jan. 2013, doi: 10.1021/es303384y.

- [22] G. Auer *et al.*, “How much energy is needed to run a wireless network?,” *IEEE Wirel. Commun.*, vol. 18, no. 5, pp. 40–49, Oct. 2011, doi: 10.1109/MWC.2011.6056691.
- [23] G. S. Kuaban, E. Gelenbe, T. Czachórski, P. Czekalski, and V. Nkemeni, “Energy performance of off-grid green cellular base stations,” *Perform. Eval.*, vol. 165, p. 102426, Aug. 2024, doi: 10.1016/j.peva.2024.102426.
- [24] S. Phillips, S. L. Woodward, M. D. Feuer, and P. D. Magill, “A regression approach to infer electricity consumption of legacy telecom equipment,” *SIGMETRICS Perform Eval Rev*, vol. 38, no. 3, pp. 61–65, Jan. 2011, doi: 10.1145/1925019.1925032.
- [25] A. A. Ibrahim, K. P. Kpochi, and E. J. Smith, “Energy Consumption Assessment of Mobile Cellular Networks,” *Am. J. Eng. Res.*, vol. 7, no. 3, pp. 96–101, 2018.
- [26] M. Alsharif *et al.*, “Optimization Analysis of Sustainable Solar Power System for Mobile Communication Systems,” *Comput. Mater. Contin.*, vol. 71, no. 2, pp. 3243–3255, 2021, doi: 10.32604/cmc.2022.022348.
- [27] F. Asghar *et al.*, “Technoeconomic analysis of standalone hybrid renewable energy systems for telecommunication sector under different climatic conditions in Saudi Arabia,” *Energy Rep.*, vol. 11, pp. 4067–4084, Jun. 2024, doi: 10.1016/j.egyr.2024.03.055.
- [28] N. R. Deevela, B. Singh, and T. C. Kandpal, “Optimization and economic analysis of solar PV based hybrid system for powering Base Transceiver Stations in India,” *Energy*, vol. 283, p. 129160, Nov. 2023, doi: 10.1016/j.energy.2023.129160.
- [29] M. Bilal Ali, A. Altamimi, S. A. A. Kazmi, and Z. A. Khan, “Leveraging Clean Power From Base Transceiver Stations for Hybrid and Fast Electric Vehicle Charging Stations System With Energy Storage Devices,” *IEEE Access*, vol. 13, pp. 39523–39556, 2025, doi: 10.1109/ACCESS.2025.3546848.
- [30] K. C. Wijesinghe, “Optimized Integration of Solar PV Energy on to Telecom Power Systems for DC and A/C buses or Energy Storages with proposed Converters to make them as profit centers,” in *2019 8th International Conference on Renewable Energy Research and Applications (ICRERA)*, Nov. 2019, pp. 545–550. doi: 10.1109/ICRERA47325.2019.8997094.
- [31] A. Rizqiawan, E. Gamia, and P. A. Dahono, “Economic Aspect of Hybrid Renewable Energy System for Base Transceiver Station,” in *2019 IEEE 13th International Conference on Telecommunication Systems, Services, and Applications (TSSA)*, Oct. 2019, pp. 102–107. doi: 10.1109/TSSA48701.2019.8985511.

- [32] K. J. Hinton, R. Ayre, and J. Cheong, *Modeling the Power Consumption and Energy Efficiency of Telecommunications Networks*, 1st ed. Boca Raton: CRC Press, 2021. doi: 10.1201/9780429287817.
- [33] K. Sharma, “Comparison of energy efficiency between macro and micro cells using energy saving schemes,” M.S. thesis, Dept. of Electrical and Information Tech. Lund University, Lund, Sweden, 2017.
- [34] Y. Yamaguchi, B. Kim, T. Kitamura, K. Akizawa, H. Chen, and Y. Shimoda, “Building stock energy modeling considering building system composition and long-term change for climate change mitigation of commercial building stocks,” *Appl. Energy*, vol. 306, p. 117907, Jan. 2022, doi: 10.1016/j.apenergy.2021.117907.
- [35] É. Mata, A. Sasic Kalagasidis, and F. Johnsson, “Building-stock aggregation through archetype buildings: France, Germany, Spain and the UK,” *Build. Environ.*, vol. 81, pp. 270–282, Nov. 2014, doi: 10.1016/j.buildenv.2014.06.013.
- [36] “Speedtest Global Index – Internet Speed around the world,” Speedtest Global Index. Accessed: Nov. 11, 2025. [Online]. Available: <https://www.speedtest.net/global-index>
- [37] W. Vereecken *et al.*, “Power consumption in telecommunication networks: overview and reduction strategies,” *IEEE Commun. Mag.*, vol. 49, no. 6, pp. 62–69, Jun. 2011, doi: 10.1109/MCOM.2011.5783986.
- [38] “Impact of progress of information society on energy consumption (Vol. 3): Current status and future forecast of network-related energy consumption and technical issues,” Japan Science and Technology Agency. Accessed: Nov. 11, 2025. [Online]. Available: <https://www.jst.go.jp/lcs/pdf/fy2020-pp-04.pdf>
- [39] G. Kamiya and P. Bertoldi, “Energy Consumption in Data Centres and Broadband Communication Networks in the EU,” JRC Publications Repository. Accessed: Nov. 11, 2025. [Online]. Available: <https://publications.jrc.ec.europa.eu/repository/handle/JRC135926>
- [40] M. Mardi Marta Dinata, Y. Yamaguchi, H. Uchida, Y. Shimoda, and A. Subekti, “Macro-Level Bottom-Up Energy Demand Modeling for Telecommunication Networks,” *IEEE Access*, vol. 12, pp. 127198–127211, 2024, doi: 10.1109/ACCESS.2024.3434976.
- [41] M. Schwartz, *Cellular Concept and Channel Allocation in Mobile Wireless Communications*, 1st ed. Cambridge, UK: Cambridge University Press, 2005.
- [42] “Investor Relations,” Telkomsel. Accessed: Nov. 12, 2025. [Online]. Available: <https://www.telkomsel.com/en/about-us/investor-relations>

- [43] "IOH: Investor Document." Accessed: Nov. 12, 2025. [Online]. Available: <https://ioh.co.id/portal/en/ioh-investor-document>
- [44] "Investor Room | XL AXIATA." Accessed: Nov. 12, 2025. [Online]. Available: <https://www.xlaxiata.co.id/en/investor-room>
- [45] "Investor," smartfren. Accessed: Nov. 12, 2025. [Online]. Available: <https://www.smartfren.com/investor/>
- [46] R. H. Hijazi and R. W. Jernigan, "Modeling Compositional Data Using Dirichlet Regression Models".
- [47] M. Maier, "DirichletReg: Dirichlet Regression for Compositional Data in R," *DirichletReg Dirichlet Regres. Compos. Data R*, Apr. 2014, doi: 10.57938/ad3142d3-2fcd-4c37-aec6-8e0bd7d077e1.
- [48] B. P. S. Indonesia, "Badan Pusat Statistik Indonesia," Badan Pusat Statistik Indonesia. Accessed: Mar. 05, 2025. [Online]. Available: <https://www.bps.go.id>
- [49] "Examine Power Consumption in the Network Operator Industry, Spanning Telcos, Webscalers, and Carrier-Neutral Operators (CNNOs) - ResearchAndMarkets.com." Accessed: Nov. 12, 2025. [Online]. Available: <https://www.businesswire.com/news/home/20221124005148/en/Examine-Power-Consumption-in-the-Network-Operator-Industry-Spanning-Telcos-Webscalers-and-Carrier-Neutral-Operators-CNNOs---ResearchAndMarkets.com>
- [50] "Listrik untuk Kehidupan yang Lebih Baik," PT PLN (Persero). Accessed: Nov. 12, 2025. [Online]. Available: <https://web.pln.co.id/en/stakeholders/statistical-report>
- [51] "PERMOHONAN INFORMASI TATA RUANG – Sistem Informasi Wilayah dan Tata Ruang Bali." Accessed: Sep. 15, 2025. [Online]. Available: <https://tarubali.baliprov.go.id/permohonan-informasi-tata-ruang/>
- [52] "Global Solar Atlas." Accessed: Sep. 08, 2025. [Online]. Available: <https://globalsolaratlas.info/download/indonesia>
- [53] "Global Wind Atlas." Accessed: Sep. 08, 2025. [Online]. Available: <https://globalwindatlas.info/en/area/Indonesia/Bali>
- [54] I. G. A. P. Eryani and A. A. R. S. Laksmi, "Water Distribution System of Petanu River Estuary for Coastal Area in Bali-Indonesia," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 434, p. 012227, Dec. 2018, doi: 10.1088/1757-899x/434/1/012227.

- [55] S. A. Kalogirou, “Chapter nine - Photovoltaic Systems,” in *Solar Energy Engineering*, S. A. Kalogirou, Ed., Boston: Academic Press, 2009, pp. 469–519. doi: 10.1016/B978-0-12-374501-9.00009-1.
- [56] S. H. Qamar, D. P. Hanak, M. Ali, J. Gomes, and K. Z. Khan, “Design, modeling and cost analysis of 8.79 MW solar photovoltaic power plant at National University of Sciences and Technology (NUST), Islamabad, Pakistan,” *Sci. Rep.*, vol. 14, no. 1, p. 25351, Oct. 2024, doi: 10.1038/s41598-024-74187-w.
- [57] A. Walker and J. Desai, “Understanding Solar Photovoltaic System Performance: An Assessment of 75 Federal Photovoltaic Systems,” NREL/TP-5C00-80881, 1838130, MainId:78659, Dec. 2021. doi: 10.2172/1838130.
- [58] J. Manwell, J. McGowan, and A. Rogers, “Wind Turbine Design and Testing,” in *Wind Energy Explained*, John Wiley & Sons, Ltd, 2009, pp. 311–357. doi: 10.1002/9781119994367.ch7.
- [59] “Vertical Axis Wind Turbine – Aeolos 1kw Vertical Wind Generator, Vertical Wind Turbine.” Accessed: Sep. 08, 2025. [Online]. Available: <https://www.windturbinestar.com/1kwv-v-aeolos-wind-turbine.html>
- [60] W. I. Ibrahim, M. R. Mohamed, R. M. T. R. Ismail, P. K. Leung, W. W. Xing, and A. A. Shah, “Hydrokinetic energy harnessing technologies: A review,” *Energy Rep.*, vol. 7, pp. 2021–2042, Nov. 2021, doi: 10.1016/j.egyr.2021.04.003.
- [61] “SMART HYDRO POWER | Hydrokinetic in-stream Turbines,” SMART HYDRO POWER. Accessed: Sep. 08, 2025. [Online]. Available: <https://www.smart-hydro.de/renewable-energy-systems/hydrokinetic-turbines-river-canal/>
- [62] T. Adefarati, G. D. Obikoya, G. Sharma, A. K. Onaolapo, and K. T. Akindeji, “Design and feasibility analysis of grid-connected hybrid renewable energy system: perspective of commercial buildings,” *Energy Syst.*, Apr. 2023, doi: 10.1007/s12667-023-00578-z.
- [63] A. Kwasinski, W. Weaver, and R. S. Balog, *Microgrids and other Local Area Power and Energy Systems*, 1st ed. Cambridge University Press, 2016. doi: 10.1017/CBO9781139002998.
- [64] “HOMER Pro Version 3.7 User Manual.” Accessed: Sep. 19, 2025. [Online]. Available: <https://www.homerenergy.com/pdf/HOMERHelpManual.pdf>
- [65] J. Huttunen, M. Pärssinen, T. Heikkilä, O. Salmela, J. Manner, and E. Pongracz, “Base Station Energy Use in Dense Urban and Suburban Areas,” *IEEE Access*, vol. 11, pp. 2863–2874, 2023, doi: 10.1109/ACCESS.2023.3234192.

- [66] A. Ayang, P.-S. Ngohe-Ekam, B. Videme, and J. Temga, “Power Consumption: Base Stations of Telecommunication in Sahel Zone of Cameroon: Typology Based on the Power Consumption—Model and Energy Savings,” *J. Energy*, vol. 2016, no. 1, p. 3161060, 2016, doi: 10.1155/2016/3161060.
- [67] M. B. Ali, S. A. A. Kazmi, A. Altamimi, Z. A. Khan, and M. A. Alghassab, “Decarbonizing Telecommunication Sector: Techno-Economic Assessment and Optimization of PV Integration in Base Transceiver Stations in Telecom Sector Spreading across Various Geographically Regions,” *Energies*, vol. 16, no. 9, Apr. 2023, doi: 10.3390/en16093800.
- [68] “Indonesia,” Climate Transparency. Accessed: Oct. 07, 2025. [Online]. Available: <https://www.climate-transparency.org/countries/asia/indonesia>
- [69] “Permen ESDM No. 2 Tahun 2024,” Database Peraturan | JDIH BPK. Accessed: Sep. 28, 2025. [Online]. Available: <http://peraturan.bpk.go.id/Details/288519/permen-esdm-no-2-tahun-2024>
- [70] “LFP-10 MAX – 10kWh Lithium Battery,” Fortress Power. Accessed: Sep. 29, 2025. [Online]. Available: <https://www.fortresspower.com/products/lfp-10-max/>
- [71] “Lithium ion battery cell price,” Our World in Data. Accessed: Sep. 29, 2025. [Online]. Available: <https://ourworldindata.org/grapher/average-battery-cell-price>
- [72] “Generac Protector RD01525ADAE ® 15kW Automatic Standby Diesel Generator w/ Mobile Link™ 120/240V Single-Phase,” Electric Generators Direct. Accessed: Sep. 29, 2025. [Online]. Available: <https://www.electricgeneratorsdirect.com/Generac-Protector-RD01525ADAE-Standby-Generator/p95377.html>
- [73] R. Alfaridzi, “Harga Solar Industri Hari Ini 2025,” PT SHA SOLO. Accessed: Sep. 29, 2025. [Online]. Available: <https://shasolo.com/harga-solar-industri-hari-ini-2023/>
- [74] “SunPower – Powering a Brighter Future | SunPower®.” Accessed: Sep. 29, 2025. [Online]. Available: <https://us.sunpower.com/>
- [75] “IRENA – International Renewable Energy Agency.” Accessed: Sep. 29, 2025. [Online]. Available: <https://www.irena.org/>
- [76] “Tariff Adjustment.” Accessed: Sep. 29, 2025. [Online]. Available: <https://web.pln.co.id/pelanggan/tarif-tenaga-listrik/tariff-adjustment>
- [77] “BI-Rate.” Accessed: Sep. 29, 2025. [Online]. Available: <https://www.bi.go.id/id/statistik/indikator/bi-rate.aspx>