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Comparative Study of Base Transceiver Stations Infrastructure Planning Using Machine Learning for Under Construction Area: A Case Study of Ibu Kota Nusantara

Alfiyah Shaldzabila Yustin, Catur Apriono*

Department of Electrical Engineering, Universitas Indonesia, Indonesia

*Correspondence: catur@eng.ui.ac.id

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ABSTRACT: Communication is a fundamental human need facilitated directly or through technologies like telephones, BTS, and satellites. Satellites, such as Starlink, provide internet access solutions, especially in remote areas, albeit at higher costs compared to traditional Base Transceiver Stations (BTS) infrastructure. Telecommunication operators face challenges deploying BTS in areas with limited access and complex financial considerations due to low rural demand, necessitating careful planning. Indonesia's capital relocation to Kalimantan aims to promote balanced national development. The future capital, Ibu Kota Nusantara (IKN), will employ advanced technologies requiring high connectivity in the region. Effective planning for BTS deployment in IKN includes predicting BTS needs. This study utilizes machine learning techniques such as Linear Regression, SVR, Random Forest, and Gradient Boosting to forecast BTS requirements. Comparative analysis reveals Random Forest performs best, with independent variables (Number of Users, Area, Population) influencing BTS needs by 82.1%, and a 45.58% prediction error. Further studies should consider model refinement through parameter tuning and variable evaluation to improve the quality of the model. The model predicted a need for 12,065 BTS units in IKN and provided stakeholders with essential planning insights. To optimize BTS development budgets, collaboration with satellite ISPs and shared tower usage should be considered.

KEYWORDS: BTS; machine learning; projection; random forest; regression

1. Introduction

Communication is a fundamental human necessity that occurs through direct or indirect means. Indirect communication, or remote interaction, utilizes supporting technologies such as telephones. Telecommunication, evolving as a process of exchanging information through transmission and reception, involves two or more individuals using wire, optical, or other electromagnetic systems [1]. Mobile telecommunications specifically require infrastructure support such as telephones, mobile phones, and signal transmitters. Signal transmitters in the realm of telecommunications include BTS, typically tower-mounted in Indonesia, and signal transmitters from satellites in outer space. Both technologies are widely utilized in Indonesia, with 556,409 BTS known to have aided internet penetration by 2022 [2]. In 2024, a new player in the internet service provider (ISP) business emerged: Starlink [3]. Starlink offers internet services using satellite signal transmitters, which are advantageous in hard-to-reach areas where BTS installation is challenging. The use of satellites for signal transmission by ISPs is not new in Indonesia, with previous satellites such as Palapa N1 (Nusantara 2) and Satria-1 serving as signal transmitters. The entry of Starlink into Indonesia's telecommunications business can pose both a threat and an opportunity. According to Muhammad Arif, Chairman of the Indonesian Internet Service Providers Association (APJII), internet penetration in Indonesia is not yet optimal, presenting a 20% opportunity for internet service providers to address the country's internet needs [4]. Starlink's introduction does not imply the replacement of BTS technology with satellite signal transmitters; rather, it serves as a complement [5]. While Starlink excels in signal transmission in rural areas, the cost for users remains relatively high compared to BTS signal transmission [6]. Therefore, the development of BTS infrastructure remains essential in meeting Indonesia's internet demands. According to reports, several mobile operators are hesitant to install BTS towers in rural regions because of difficulties in access and low population density, along with financial limitations [7]. Effective planning for BTS deployment requires thorough consideration of various factors to ensure efficient allocation of funds. Machine learning technology can play a pivotal role in facilitating this planning process.

Machine learning is a part of artificial intelligence (AI) that focuses on enhancing system performance by optimizing processes. When applied effectively, this technology enables users to make more accurate predictions rather than random guesses [8]. There are various machine learning algorithms tailored to different scenarios, such as facial recognition, optimizing BTS placement, and modeling for predicting other phenomena [9–10]. In this study, BTS data from 25 Indonesian provinces with extensive internet coverage, based on data from Badan Pusat Statistik (BPS) and Indonesia’s Ministry of Telecommunication and Information (Kominfo), will be utilized. Supporting variables influencing BTS requirements include population size, number of mobile phone users, and area size. The dataset will be used for modeling using machine learning algorithms such as Linear Regression, Support Vector Regression (SVR), Random Forest, and Gradient Boosting. These models aim to predict the needed number of BTS in areas still lacking internet access, including in the infrastructure planning for the IKN.

Employing machine learning predictions in BTS development planning is expected to advance telecommunications management by utilizing ICT, particularly Machine Learning, to forecast BTS (Base Transceiver Station) requirements. It strives to establish itself as a pivotal reference for future advancements in this specialized domain. The study's findings are poised to provide fresh perspectives and practical applications for telecommunications institutions, potentially enhancing operational efficiencies and streamlining business processes. By adopting the predictive models and methodologies proposed in this research, these institutions can make well-informed decisions regarding BTS infrastructure deployment, thereby optimizing their operational strategies. Implementing the insights gleaned from this study promises to refine the planning and execution of BTS networks, ultimately leading to improved service delivery and operational effectiveness. This proactive approach not only addresses current telecommunications challenges but also serves as a reference for supporting future innovations and developments in the field.

2. Literature Review

2.1. Previous research.

A crucial step in this research was to review previous studies, which served as inspiration and provided information for the development of further research. These studies were then reviewed to understand the impact of using Machine Learning algorithms and to draw relevant connections for this study. Several references that were used in the development of the research methodology are as follows:

Table 1. Result of previous research reviews.

Author/Research Title	Main Topic	Machine Learning Algorithms	Correlation with the Research
D. Alekseeva, N. Stepanov, A. Veprev, A. Sharapova, E. S. Lohan and A. Ometov, "Comparison of Machine Learning Techniques Applied to Traffic Prediction of Real Wireless Network," [11]	Comparing several Machine Learning methods to predict wireless network traffic	Linear Regression, Support Vector Machines (SVM), Bootstrap Aggregation (Bagging), Gradient Boosting, Huber Regression, Bayesian Regression, and Random Forest	Topics related to the use of Machine Learning in the field of telecommunications. Comparing various types of Machine Learning methods for Regression modeling.
C. E. G. Moreta, M. R. C. Acosta and I. Koo, "Prediction of Digital Terrestrial Television (DTT) n Coverage Using Machine Learning Regression, [12]	Predicting DTT coverage using Machine Learning regression	Random Forest regression, adaptive boosting (AdaBoost), and K-nearest neighbors (KNN)	Topics related to the use of Machine Learning in the field of telecommunications. Comparing various types of Machine Learning methods for Regression modeling
O. Wisesa, A. Adriansyah and O. I. Khalaf, "Prediction Analysis Sales for Corporate Services Telecommunications Company using *Gradient Boost* Algorithm," [13]	Sales data prediction and analysis in the telecommunications sector	Gradient Boost	Application of Gradient Boost algorithm in telecommunications.
I. Naseem, R. Togneri, and M. Bennamoun, "Linear Regression for Face Recognition," [14]	Classification for face recognition	Linear Regression	Application of Linear Regression Algorithm.
A. Malakar, A. Kumar and S. Vyas, "Comparative Study of Proposed Linear Regression Algorithm to Scikit-Learn Algorithm," [15]	Linear regression for comparing human head size and brain weight	Proposed algorithm vs Sklearn algorithm	Using regression and comparing model performance of various Machine Learning techniques.
A. Yaqin, M. Rahardi, F. F. Abdulloh, Kusnawi, S. Budiprayitno and S. Fatonah, "The Prediction of COVID-19 Pandemic Situation in Indonesia Using SVR and SIR Algorithm," [16]	Regression for predicting COVID-19 cases	SVR vs. SIR	Conducting regression and comparisons of machine learning model.
J. Qiao *et al.*, "Mobile Network User Perception Prediction based on *Random Forest* Algorithm," [17]	Prediction for Telecommunications Service User Perception	Random Forest	Prediction modeling with Random Forest

Based on the data in Table 1, this study performed prediction modeling using Machine Learning by comparing several algorithms that had proven to yield good results. The Machine Learning algorithms compared were Linear Regression, SVR (Support Vector Regression), Gradient Boosting, and Random Forest. The selection was also based on data used in similar literature relevant to this study's data.

2.2. Base Transceiver Station (BTS).

A Base Transceiver Station (BTS) is a critical telecommunications infrastructure that facilitates wireless communication between network operators and communication devices. BTS is also known as Base Station (BS) or Radio Base Station (RBS). Its functions include transmitting and receiving radio signals from devices such as landline phones, mobile phones, and other gadgets. These radio signals are then converted into digital signals to be sent to other terminals as messages or data [18]. In Indonesia, BTS is commonly located on towers of various shapes, including four-legged towers, three-legged towers, or single poles, as depicted in Figure 1. A tower is a specialized building designed to support telecommunication equipment, with its design or construction adapted to the needs of telecommunication operations [20]. The placement of BTS towers requires careful planning as it affects the strength of received and transmitted signals, and any errors can incur significant costs for relocation.

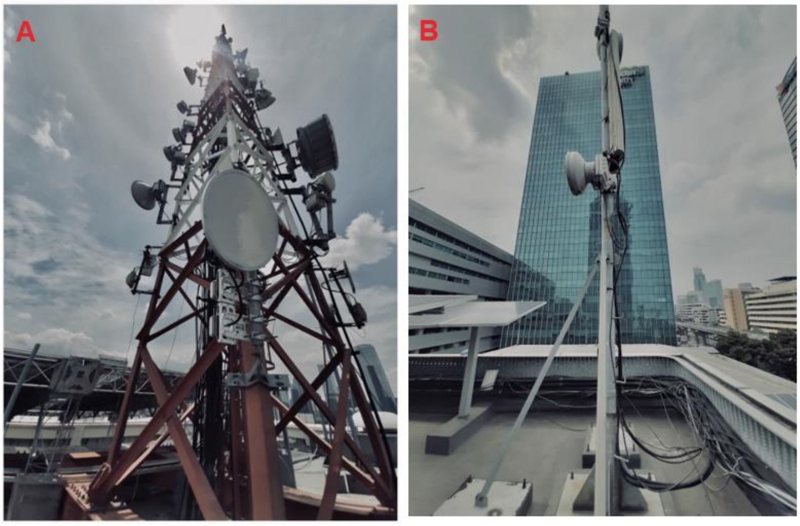

Figure 1. (**A**) Four-legged BTS tower; (B) Single pole BTS tower [19].

2.3. Machine learning.

Machine Learning has many types and applications. According to its operation, it can be categorized into supervised learning and unsupervised learning. Furthermore, in terms of usage, it is generally divided into two functions: clustering and regression functions. In this study, machine learning models will be used for regression to create models based on existing data that can predict new data. Here are several machine learning models used in this research:

2.3.1. Linear regression.

Linear regression is a type of supervised learning used to model systems based on existing data. There are two types: simple linear regression and multiple linear regression. Simple linear regression uses one independent variable to predict a dependent variable. In comparison, multiple regression is a statistical analysis method that uses more than one independent variable to predict a dependent variable [21].

2.3.2. Random forest.

Random Forest is a supervised machine-learning technique used for classification and regression. This method employs ensemble learning principles by constructing a "forest" of numerous decision trees. The algorithm utilizes bagging techniques to mitigate the risk of overfitting. Each decision tree in a Random Forest operates independently, using different subsets of the original data. The final prediction in Random Forest Regression is obtained by averaging the predictions from all the trees in the forest [22].

2.3.3. Support Vector Regression (SVR).

Support Vector Regression (SVR), also known as kernel-based methods, are a machine learning technique based on statistical learning theory. SVR offers advantages over Artificial Neural Networks (ANNs), such as maximizing generalization capability, resilience to outliers, and avoiding overtraining issues. SVR and their variants have been extensively researched and widely used to tackle pattern classification problems and function approximation [23].

2.3.4. Gradiennt boosting.

Gradient boosting is a machine learning technique commonly used for regression and classification problems. This technique produces a final prediction model by combining multiple weak predictors. The concept originated from observations by Breiman (1997) and was further developed by Jerome H. Friedman (2001, 2002). Gradient boosting works by optimizing the cost function iteratively, selecting functions that move in the direction of the negative gradient at each iteration [24].

2.4. Telecommunication business in Indonesia.

The telecommunications business in Indonesia is currently experiencing saturation, characterized by difficulties in acquiring new subscribers for mobile operators. Merger and acquisition activities among operators are becoming prevalent as they strive to maintain market share. The COVID-19 pandemic has significantly impacted the business and financial aspects of telecommunications companies in Indonesia. Mobile operators are increasingly focusing on internet data packages as part of their strategy, competing primarily on internet speed and accessibility. In addition to existing mobile operators, Indonesia saw the entry of a new competitor in 2024, Starlink, operating in the Internet service provider (ISP) sector. Starlink specializes in providing internet services through satellite signal transmission. However, the introduction of Starlink does not imply a replacement of BTS (Base Transceiver Station) used extensively by mobile operators in Indonesia. Mobile operators face challenges in investing in BTS infrastructure due to inaccessible areas and financial viability concerns. One non-technical approach to optimize infrastructure investment is through shared tower/mast usage among different mobile operators.

3. Materials and Method

3.1. Materials.

3.1.1. Data mining and processing.

In this study, data obtained from the Indonesian Central Statistics Agency (BPS) and the Ministry of Communication and Information of the Republic of Indonesia (Kominfo) are utilized. Population, user counts, and area size data were collected through surveys conducted by the Central Statistics Agency. Meanwhile, the number of BTS (Base Transceiver Station) data was obtained from statistics provided by the Ministry of Communication and Information of the Republic of Indonesia (Kominfo). Statistical data were gathered from multiple sources and consolidated to form the dataset used in the machine learning process using Microsoft Excel. The dataset comprises data from 25 provinces with the highest coverage of internet network areas, as indicated in Table 2. The dataset utilized in the machine learning process (refer to Table 3 shows the sample of the dataset) is based on surveys conducted in 2018, 2019, 2020, 2021 and 2022.

Table 2. Percentage of villages/districts with signal coverage by province in Indonesia in 2021 [2, 25].

Province	Population (Thousand Person)	Percentage of Villages/Districts with Signal Coverage	Number of Villages/Districts Without Signal
Kepulauan Bangka Belitung	2,032.9	100.00%	0
Bali	5,470.8	100.00%	0
Jawa Tengah	12,061.5	99.94%	5
Jawa Barat	48,782.4	99.92%	5
Banten	40,878.8	99.87%	2
Jawa Timur	3,712.9	99.80%	17
Riau	6,493.6	99.79%	4
DI Yogyakarta	36,742.5	99.77%	1
DKI Jakarta	10,609.7	99.63%	1
Lampung	1,473.2	99.62%	10
Nusa Tenggara Barat	2,702.2	99.57%	5
Aceh	5,333.7	99.51%	32
Kalimantan Selatan	2,638.6	99.35%	13
Jambi	2,118.2	99.10%	14
Sumatera Selatan	3,585.1	98.84%	38
Kepulauan Riau	9,081.8	98.56%	6
Bengkulu	8,550.9	98.55%	22
Sumatera Barat	5,580.2	98.53%	17
Sulawesi Selatan	2,659.2	98.36%	50
Gorontalo	5,390.0	97.82%	16
Sulawesi Utara	9,139.5	97.66%	43
Sumatera Utara	14,936.2	97.58%	148
Sulawesi Tenggara	4,362.7	95.67%	100
Kalimantan Timur	1,181.0	95.47%	47
Sulawesi Tengah	1,436.8	95.35%	94

3.2. Method.

3.2.1. Modeling.

The modeling was conducted using the dataset that consists of 125 sets of independent variables and dependent variables in the regression process using machine learning (the dataset sample can be seen in Table 3). The machine learning methods used are linear regression, random forest, SVR, and gradient boosting. These four methods will then be compared to choose the best-performing one. The method for selecting the best model involves comparing the values of Mean Squared Error, Integrated Time and Absolute Error, and $\boldsymbol{R^2}$ score. The parameters used in machine learning can be seen in Table 4. The machine learning process in this research utilizes Anaconda JupyterLab & Notebook software with the Python programming language.

Table 3. Sample of dataset (population count, area size, number of BTS, and number of users per province for the years 2018, 2019, 2020, 2021 and 2022) [2, 25-28].

Province	Population Count (Thousand person)	Area Size (km^2)	Number of BTS (pcs)	User Count (person)
Kepulauan Bangka Belitung 2018	1,948.6	16,424.06	3,655	1,333,037
Kepulauan Bangka Belitung 2019	1,971.8	16,424.06	4,144	1,336,289
Kepulauan Bangka Belitung 2020	2,010.7	16,424.06	4,944	1,339,327
Kepulauan Bangka Belitung 2021	2,032.9	16,424.06	5,697	1,386,844
Kepulauan Bangka Belitung 2022	2,060.1	16,424.06	5,012	1,507,169
Bali 2018	4,985.1	5,780.06	8,170	3,389,369
Bali 2019	5,045.7	5,780.06	9,813	3,512,312
Bali 2020	5,414.4	5,780.06	17,050	3,786,290
Bali 2021	5,470.8	5,780.06	18,746	3,919,828
Bali 2022	5,541.4	5,780.06	17,020	4,035,247
Jawa Tengah 2018	12,530.8	32,800.69	44,841	7,577,375
Jawa Tengah 2019	12,714.3	32,800.69	43,039	7,839,637
Jawa Tengah 2020	11,904.6	32,800.69	57,759	7,246,330
Jawa Tengah 2021	12,061.5	32,800.69	68,045	7,569,797
Jawa Tengah 2022	12,252.0	32,800.69	58,815	7,982,178
Jawa Barat 2018	48,475.5	35,377.76	50,878	31,513,923
Jawa Barat 2019	49,023.2	35,377.76	97,589	32,472,968
Jawa Barat 2020	48,274.2	35,377.76	104,840	31,296,164
Jawa Barat 2021	48,782.4	35,377.76	101,377	33,089,102
Jawa Barat 2022	49,405.8	35,377.76	61,458	34,766,861
Banten 2018	39,521.9	9,662.92	24,949	25,392,821
Banten 2019	39,744.8	9,662.92	29,808	25,917,584
Banten 2020	40,665.7	9,662.92	32,471	26,188,711
Banten 2021	40,878.8	9,662.92	37,286	27,879,342
Banten 2022	41,150.0	9,662.92	31,654	28,907,875
Jawa Timur 2018	3,818.3	47,803.49	52,952	2,316,181
Jawa Timur 2019	3,868.6	47,803.49	67,278	2,404,722
Jawa Timur 2020	3,668.7	47,803.49	70,487	2,267,990
Jawa Timur 2021	3,712.9	47,803.49	81,456	2,338,756
Jawa Timur 2022	3,761.9	47,803.49	70,810	2,453,511

Table 4. Machine learning method and parameters.

Method	Parameters
Linear Regression	default
Random Forest	n_estimators=1500, random_state=42
SVR	kernel='rbf', C=100, gamma=0.1
Gradient Boosting	n_estimators=1500, random_state=42

3.2.2. Testing.

Several types of tests are applied to the model generated by the selected best method. The tests applied to the model include:

a. Normality Assumption Test
b. Homoscedasticity Test (Breusch-Pagan)
c. Multicollinearity Test (VIF)
d. t-test for coefficient significance
e. F-test for model significance

3.2.3. Prediction.

The tested model is then used to predict the number of BTS requirements by inputting a new case, namely the infrastructure development plan in IKN with specifications, as shown in Table 5.

Table 5. Projection of BTS procurement planning parameters in IKN 2025-2029 [29].

Parameter	Value
Population Count	1,280,000 Residents
User Count	85% Total Residents[1]
Area Size	256,142.72 km^2

[1] author's assumptions based on other province data.

The determination of the number of users and skill proficiency indicators is based on one of the smart city criteria in IKN [30], namely smart citizen, where it is expected that at least 85% of the total population possess and master the use of mobile phones. In the process of analyzing prediction results, it is necessary to consider the following limitations:

a. The predictions made are general and do not consider mobile network development/planning variables such as spectrum, BTS types, propagation, and other technical variables.
b. The predictions are assumed to be based on ideal conditions without considering the region's topological characteristics, such as terrain curvature and variations in BTS construction height, which in this study pertain to the IKN area.
c. The prediction results cannot be used as the primary reference for the required number of BTS because they are still predictions and subject to other limitations.

4. Result and Discussion

4.1. Modeling.

Table 6. Various machine learning modeling results.

Method	Parameters			
	MSE	RMSE	MAPE	R^2
Linear Regression	468,564,723.89	21,651.34	121.12	0.368
Random Forest	132,551,035.97	11,513.52	45.58	0.821
SVR	866,264,516.96	29,431.77	83.76	-0.169
Gradient Boosting	159,504,308.39	12,631.86	40.62	0.785

Based on Table 6, it can be observed that among the four methods used, Random Forest performs the best with the smallest MSE, RMSE, and R^2 that close to 1. The high MSE and RMS values could be due to the use of real data, as observed in previous studies [11]. Therefore, the modeling results from the Random Forest machine learning method will be tested in the next stage. The performance of the random forest method has been proven to yield good results based on several previous studies [12, 17].

4.2. Regression testing.

4.2.1 Normality assumption test (Shapiro-Wilk):

Table 7. Shapiro-Wilk Test Result

Parameters	Value
Statistic test	0.796
P-value	0.00015

The low p-value shown in Table 7 indicates that there is enough evidence to reject the hypothesis that the data follows a normal distribution. This condition suggests that the data may not be normally distributed.

4.2.2 Homoscedasticity test (Breusch-Pagan):

Table 8. Breusch-Pagan test result.

Parameters	Value
LM Statistic	15.60
LM Test P-value	0.00041
F-statistic	11.50
F Test P-value	8.34e-05

The low P-value shown in Table 8 indicates that there is enough evidence to reject the assumption of homoscedasticity, suggesting that the residual variance is not constant. This condition may arise due to the data being influenced by various non-technical factors, which contribute to the non-constant variance of the error terms.

4.2.3 Multicollinearity test (VIF):

Table 9. Multicollinearity test result.

	Features	VIF
0	Population Count	418.63
1	User Count	415.72
2	Area Size	1.17

Based on the provided data (Table 9), the variable Population Count and User Count VIF Score indicate that these variables exhibit significant multicollinearity in your Random Forest model, indicating a strong correlation between Population Count and User Count. The variable Area Size has a low VIF value, indicating that Area Size does not suffer from significant multicollinearity with other variables in the model. It suggests that Area Size can be considered more independent in its influence on predicting the required number of BTS.

4.2.4 F-test for model significance.

Table 10. F Model significance test result.

Parameters	Value
F-statistic	8.15
p-value	6.84e-05

Based on the provided data (Table 10), The F-statistic result of 8.15 indicates that the model can explain some variability in the data. The P-value of 6.84e-05 is smaller than the significance level of 0.05, which means the null hypothesis can be rejected. It indicates that the Random Forest model as a whole has statistical significance in predicting the number of BTS required. It can be concluded that the variables Population Count, User Count, and Area Size have statistical significance in predicting the number of BTS required.

4.3. Prediction result.

The result using the random forest modeling showed that the influence of the independent var iables (Number of Users, Area, and Population) on the dependent variable (Number of BTS) i s 82.1%, with a percentage error of 45.58% between the predicted results and the actual data.

It can be determined that the predicted number of BTS units needed to be built in IKN is 12,0 65 BTS. Although the percentage influence of the independent variables on the dependent var iable is quite substantial, it should be noted that these results are still predictions with several limitations, assuming general and ideal conditions without considering other technical variabl es related to network construction. This figure will need further adjustment and may potential ly decrease with additional processes, such as maximizing BTS capacity and collaborating wi th satellite signal transmitter technology. The cost of BTS infrastructure development can be r educed by utilizing shared towers, eliminating the need to construct towers for each BTS. Fur ther development can involve optimizing BTS mapping and placement to reach more users w ith fewer BTS by strategically locating BTS in optimal positions. By conducting this study to predict the number of BTS infrastructures needed, it is hoped to provide an illustration of usin g machine learning methods to predict BTS needs in IKN to provide smart city technology pl ans [30]. It is expected that this will serve as information for relevant stakeholders in consider ing the fulfilments of connectivity in the IKN area by building an appropriate number of BTS units, considering the predicted population, number of service users, and area of IKN.

5. Conclusion

The planning of telecommunication infrastructure development such as BTS can be facilitated by machine learning using data such as existing BTS count, Population, User count, and Area Size. Comparative analysis shows that the random forest machine learning method provides the best modeling results compared to linear regression, Gradient Boosting, and SVR methods. Despite the superior performance of the random forest method, further fine-tuning is still needed through parameter adjustments and evaluation of variables used to achieve an even better model. The modeling results can be utilized to predict the BTS infrastructure needs in IKN, estimated at 12,065 units. In BTS development planning, mobile operators can collaborate both among themselves and with Internet Service Providers (ISPs) utilizing satellite media. Utilizing shared towers can be an option for cost-efficient BTS infrastructure development.

Competing Interest

The authors declare no financial or non-financial competing interests.

References

[1] Law No. 36 Year 1999 - Telecommunication | JDIH BPK. (accessed on 23 June 2024). Available online: https://peraturan.bpk.go.id/Details/45357/uu-no-36-tahun-1999.

[2] Ministry of Communication and Informatics of the Republic of Indonesia, Directorate General of Postal and Informatics, Directorate of Postal and Informatics Control, Indonesian Telecommunications Statistics 2023. 2024, pp. 96–99.

[3] The Future of Starlink in Indonesia. (accessed on 23 June 2024) Available online: https://news.detik.com/kolom/d-7401468/masa-depan-starlink-diindonesia#:~:text=Pada%20Minggu%2C%2019%20Mei%202024.

[4] 20 Percent of Indonesians Without Internet Access Are Spread Across the Eastern Region – APJII. (accessed on 23 June 2024) Available online: https://apjii.or.id/berita/d/20-persen-warga-indonesia-belum-terakses-internet-tersebar-di-timur.

[5] Kominfo: Indonesia Still Needs BTS Towers Despite the Presence of Starlink. (accessed on 23 June 2024). Available online: https://tekno.kompas.com/read/2024/06/12/09000087/kominfo--indonesia-masih-butuh-bts-meski-sudah-ada-starlink?page=all.

[6] Comparing Starlink Internet Prices with Local ISPs IndiHome, Biznet, and First Media. (accessed on 23 June 2024) Available online: https://tekno.kompas.com/read/2024/05/17/13000007/membandingkan-harga-internet-starlink-dengan-isp-lokal-indihome-biznet-dan.

[7] With BTS Towers, Residents of Doi Island No Longer Need to Cross the Sea for Internet Access. (accessed on 23 June 2024). Available online: https://news.detik.com/berita/d-7085058/ada-bts-warga-pulau-doi-tak-perlu-lagi-sebrangi-laut-buat-internetan.

[8] AI vs. machine learning vs. deep learning vs. neural networks | IBM. (accessed on 13 May 2024). Available online: https://www.ibm.com/think/topics/ai-vs-machine-learning-vs-deep-learning-vs-neural-networks.

[9] Naseem, I.; Togneri, R. Bennamoun, M. (2020). Linear Regression for Face Recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *32*, 2106–2112. https://doi.org/10.1109/TPAMI.2010.128.

[10] Afuzagani, D.; Suyanto, S. (20200. Optimizing BTS Placement Using Hybrid Evolutionary Firefly Algorithm. 2020 8th International Conference on Information and Communication Technology (ICoICT), https://doi.org/10.1109/icoict49345.2020.9166273.

[11] Alekseeva, D.; Stepanov, N.; Veprev, A.; Sharapova, A.; Lohan, E.S.; Ometov, A. (2021). Comparison of Machine Learning Techniques Applied to Traffic Prediction of Real Wireless Network. *IEEE Access*, *9*, 159495–159514. https://doi.org/10.1109/ACCESS.2021.3129850.

[12] Moreta, C.E.G.; Acosta, M.R.C.; Koo, I. (2019). Prediction of Digital Terrestrial Television Coverage Using Machine Learning Regression. *IEEE Transactions on Broadcasting*, *65*, 702–712. https://doi.org/10.1109/TBC.2019.2901409.

[13] Wisesa, O.; Adriansyah, A.; Khalaf, O.I. (2020). Prediction Analysis Sales for Corporate Services Telecommunications Company using Gradient Boost Algorithm. 2020 2nd International Conference on Broadband Communications, Wireless Sensors and Powering (BCWSP), Yogyakarta, Indonesia, pp. 101–106, https://doi.org/10.1109/BCWSP50066.2020.9249397.

[14] Naseem, I.; Togneri, R.; Bennamoun, M. (2010). Linear Regression for Face Recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *32*, 2106–2112. https://doi.org/10.1109/TPAMI.2010.128.

[15] Malakar, A.; Kumar A.; Vyas, S. (2023). Comparative Study of Proposed Linear Regression algorithm to Scikit-Learn Algorithm. 2023 10th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON), Gautam Buddha Nagar, India, pp. 301–304. https://doi.org/10.1109/UPCON59197.2023.10434301.

[16] Yaqin, A.; Rahardi, M.; Abdulloh, F.F.; Kusnawi, Budiprayitno, S.; Fatonah, S. (2022). The Prediction of COVID-19 Pandemic Situation in Indonesia Using SVR and SIR Algorithm. 2022 6th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE), Yogyakarta, Indonesia, pp. 570–573. https://doi.org/10.1109/ICITISEE57756.2022.10057813.

[17] Qiao, J.; Zhu; J.; Cheng; X.; Xu; L.; Lyu; F.; Liu; L.; Wang; Z.; Di, Z. (2021). Mobile Network User Perception Prediction based on Random Forest Algorithm. 2021 International Conference on Information and Communication Technologies for Disaster Management (ICT-DM), Hangzhou, China, pp. 43–48, https://doi.org/10.1109/ICT-DM52643.2021.9664054.

[18] Definition, Types, and Components of BTS Towers You Should Know. (accessed on 23 June 2024). Available online: https://www.baktikominfo.id/id/detail-berita/pengertian-macam-dan-komponen-pada-tower-bts-yang-sebaiknya-anda-tahu.

[19] BTS Tower on Top of Government Building? (accessed on 23 June 2024). Available online: https://www.djkn.kemenkeu.go.id/kpknl-jakarta2/baca-berita/20185/Menara-BTS-diatas-Gedung-pemerintah.html.

[20] Minister of Communication and Informatics Regulation No: 02/PER/M.KOMINFO/3/2008 on Guidelines for the Construction and Use of Shared Telecommunication Towers. (accessed on 23 June 2024) Available online: https://peraturan.bpk.go.id/Details/159668/permenkominfo-no-2permkominfo32008-tahun-2008.

[21] Ostertagová, E. (2012). Modelling using polynomial regression. *Procedia Engineering, 48*, 500−506. https://doi.org/10.1016/j.proeng.2012.09.545.

[22] An Investigation of How Well Random Forest Regression Can Predict Demand of Groceries (accessed on 23 June, 2024). Available online: https://corporatefinanceinstitute.com/resources/knowledge/ecommerce-.

[23] Li, N.; Lu, G.; Li, X.; Yan, Y. (2015). Prediction of Pollutant Emissions of Biomass Flames Through Digital Imaging, Contourlet Transform, and Support Vector Regression Modeling. *IEEE Transactions on Instrumentation and Measurement, 64*, 2409−2416. https://doi.org/10.1109/TIM.2015.2411999.

[24] Li, W.; Wang W.; Huo, W. (2020). RegBoost: a gradient boosted multivariate regression algorithm. *International Journal of Crowd Science, 4*, 60−72. https://doi.org/10.1108/IJCS-10-2019-0029.

[25] Number of Villages/Subdistricts by Province and Mobile Phone Signal Reception, 2021 - Statistical Table. (accessed on 23 June 2024). Available online: https://www.bps.go.id/id/statistics-table/3/TDJsTlFXOXhXVW81VEZoa1EwUk1iRUphZEVkRFVUMDkjMw==/banyaknya-desa-kelurahan-menurut-provinsi-dan-penerimaan-sinyal-internet-telepon-seluler.html?year=2021.

[26] Area Size and Number of Islands by Province, 2021 - Statistical Table. (accessed on 23 June 2024). Available online: https://www.bps.go.id/id/statistics-table/3/VUZwV01tSlpPVlpsWlRKbmMxcFhhSGhEVjFoUFFUMDkjMw==/luas-daerah-dan-jumlah-pulau-menurut-provinsi--2021.html.

[27] Directorate of Postal and Informatics Control, Directorate General of Postal and Informatics - Ministry of Communication and Informatics, Data Book on Postal and Informatics Implementation 2021.

[28] Directorate of Postal and Informatics Control, Directorate General of Postal and Informatics - Ministry of Communication and Informatics, Data Book on Postal and Informatics Implementation 2022.

[29] Population of IKN Projected to Reach 1.91 million by 2045. (accessed on 23 June 2024). Available online: https://dataindonesia.id/varia/detail/penduduk-ikn-diproyeksikan-mencapai-191-juta-jiwa-pada-2045.

[30] Deputy for Green and Digital Transformation - Ministry of Public Works and Public Housing, Smart City Blueprint of Nusantara. 2023. (accessed on 23 June 2024). Available online: https://www.ikn.go.id/storage/thd/blueprint/cetak_biru_kota_cerdas_nusantara.pdf.