Optimizing Call Setup Success (CSSR) Parameters In Mobile Communications Using K-Nearest Neighbor (K-NN)

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Abstract— The evaluation of the mobile communication network inside the cellular communication system, often known as the Global System for Mobile Communication, is crucial to achieve optimal call quality. The Call Setup Success Rate (CSSR) is a measure that plays a significant role in determining the performance of the mobile network, alongside various other factors. The mobile network's performance may decrease if the Call Setup Success Rate (CSSR) number is below the expected standard. The CSSR outcome is influenced by multiple variables that lack a specific formula or exhibit no discernible relationship with one another. The individual responsible for optimizing decisions in the real case is an operator or an engineer who relies on their experience to inform their choices. Nevertheless, even those with previous expertise in this domain may encounter difficulties determining the most effective approach for optimizing CSSR parameters since they must consider the interconnections among the many inherent values in these parameters. In order to achieve this objective, it is necessary to employ pattern recognition algorithms, among which the k-nearest Neighbor (k-NN) technique is included. In this study, the k-nearest Neighbor method will be employed to assist novice engineers in determining the optimization method for enhancing CSSR performance. Certain data from the OMC-R are utilized for the purpose of enhancing the performance of the CSSR and determining the feasibility of employing the k-NN pattern recognition approach to improve the CSSR. The efficacy of the k-Nearest Neighbors (k-NN) algorithm in providing an optimal solution, as determined by the operator or engineer on behalf of the telecommunication service provider, serves as a key indicator of the system's overall success. The implementation of CSSR optimization utilizing the k-NN algorithm decision has achieved a successful outcome, with 89.65% of the total data being accurately processed.

Keywords— Mobile Communication, CSSR, K-NN, Optimization

1. Introduction

The performance of the mobile cellular communication system, known as the Global System for Mobile Communication, necessitates careful consideration to ensure the appropriate maintenance of call quality, encompassing voice calls, video calls, and data communications. The performance of the mobile network is influenced by several elements, among which the Call Setup Success Rate (CSSR) is a significant factor. If the CSSR (Call Setup Success Rate) exhibits poor performance, it will, therefore, result in a decline in the overall performance of the mobile network. Hence, optimizing the CSSR value is imperative to enhance the performance of mobile communication. The CSSR value is influenced by various parameters that lack a formulaic relationship or are unconnected. In the field, optimization decisions are made by the operator or engineer, drawing upon their experiential knowledge. Nevertheless, those lacking expertise in this domain may encounter challenges when attempting to make informed decisions regarding the optimization of CSSR parameters, particularly in relation to the interdependencies among the different values within these parameters. Conversely, using pattern recognition algorithms can aid in the decision-making process by analyzing the fluctuations in the values of the CSSR parameters. The pattern recognition algorithms commonly utilized in the field include Artificial Neural Networks (ANN), Fuzzy, and k-nearest Neighbor (k-NN) [1] [2] [3]. The k-nearest Neighbor technique will facilitate CSSR optimization decisions for multiple pattern recognition algorithms. This study refers to several previous studies regarding mobile communication networks by analyzing the factors that cause low-value Handover Successful Rate (HOSR) to be optimized [4], analyzing radio parameters for optimization, and analyzing call quality using Tems Investigation [5]. The three studies only analyzed network performance before the optimization steps. Subsequent research on the application network application of Artificial Neural Networks (ANN) as an analytical tool for optimizing the performance of Call Setup Success Rate (CSSR) on mobile communications [6] has carried out network performance analysis with optimization steps. An important consideration for cellular telecommunication service providers is the performance evaluation of the mobile communication network. The mobile network performance can be evaluated by examining the Call Setup Success Rate (CSSR) [7]. This study aims to optimize the performance of the Call Setup Success Rate (CSSR) by utilizing statistical data obtained from monitoring results from the Operation and Maintenance Center - Radio (OMC-R). These monitoring results serve as parameters for CSSR improvement. The CSSR (Call Setup Success Rate) parameters encompass the following metrics: Call Attempt, SDCCH (Standalone Dedicated Control Channel) Block Rate, SDCCH Drop Rate, TCH (Traffic Channel) Availability, TCH Blocking, Total Traffic, BH TCH (Busy Hour Traffic Channel), and Max Available Circuit Switch [8] [9] [10] [11]. The parameters mentioned are utilized for the purpose of optimizing the performance of Call Setup Success Rate (CSSR) and determining the appropriate approach for CSSR optimization. To do this, a pattern recognition algorithm called k-Nearest Neighbor is employed. The measure of success for this system is achieved when the k-nearest Neighbor algorithm can generate an optimized choice based on the optimization target set by the operator (engineer) representing the telecommunication service provider.

2. METHODS

2.1 System Design

Prior to the development of a Call Setup Success Rate (CSSR) optimization system on figure 1, it is important to establish a comprehensive system design. The data collected from the Servo Analytic application pertains to the Call Setup Success Rate (CSSR) performance metrics. This data was gathered over a period of three months, specifically from 1 January 2013 to 31 March 2013. The measurements were conducted at BTS Unnes Sekaran, DCS Salatiga. Each Base Transceiver Station (BTS) is divided into three sectors, resulting in three CSSR data points each day from each BTS. The cumulative CSSR data collected between January and March amounts to 540 data points, calculated by multiplying the number of base transceiver stations (BTS) by the number of days (90) and the number of CSSR data points (3). Each member of BTS faces distinct challenges and hails from various geographical areas. Consequently, the preprocessing and testing of CSSR data are conducted independently, considering the specific issues and geographical locations of each Base Transceiver Station (BTS). Before conducting the testing phase, it is essential to establish reference data, which will serve as the training data for the testing process. Within this system, the reference data chosen for each Base Transceiver Station (BTS) consists of 15 reference data points. These reference data points are produced through the analysis of 5 CSSR data sets, which have been collected over a span of 5 consecutive days. The process of optimizing CSSR involves the formation of reference data, followed by pattern recognition using the k-nearest Neighbor algorithm. This entails determining the distance parameter to calculate the shortest distance between the test data and reference data, as well as selecting the appropriate k-value parameter for testing purposes. During the testing phase, there are two distance parameters available for selection: Euclidean distance and Hamming distance. The Euclidean distance is an equation measuring the distance between 2 points in n-dimensional space [12]. In K-Nearest Neighbor, the smaller the distance between 2 points means the more similarities between the data they represent [14]. In continuous systems, distances are measured by Euclidean distance concepts such as lengths, angles, and vectors [13]. In the binary world, the distance between two binary words is calculated using the Hamming distance. The Hamming distance is the number of bit value differences between two binary sequences of the same size. In other words, the hamming distance d(x,y) between the two code words x and y is the number of different coordinate positions between the two code words x and y [14] [15].

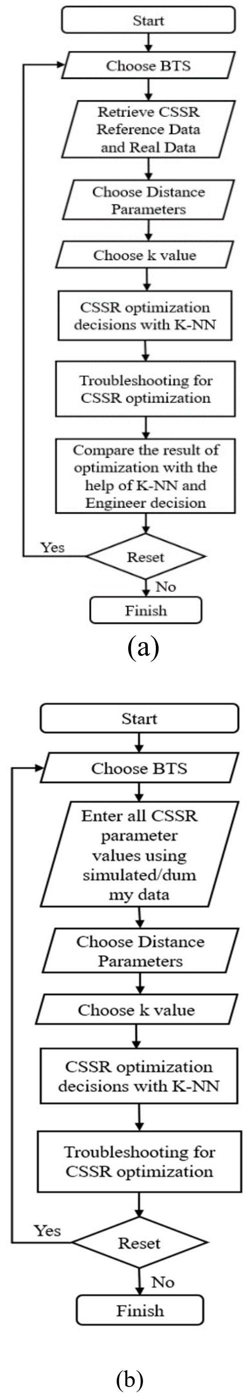

Figure. 1. CSSR optimization system flow chart (a) using real data (b) using simulated/dummy data

2.2 Training and Acquisition of Data

Reference data is formed from CSSR data that has been previously stored. Before the testing process can occur, reference data must first be formed. The reference data for each BTS is different because each BTS has different problems and regional locations. The reference data for each BTS consists of CSSR data, with several target classes for optimization decisions depending on the problems in each BTS. There are 4 CSSR optimization target classes where each optimization target class is encoded in numeric form, namely

Normal (1), TCH addition (2), SDCCH addition (3), and HCR (4). For example, in Table 3.1, there is an example of reference data on BTS UNNES Sekaran. In the table, BTS UNNES Now has 2 CSSR optimization target classes, and there are 15 reference data consisting of 7 additional TCH optimization target classes (2) and 8 Normal optimization target classes (1). Before the reference data is stored, normalization is carried out for each existing CSSR parameter using formula 1.

$$Xs = \frac{X - Xmin}{Xmax - Xmin} \quad (1)$$

The parameter value after normalization is denoted as Xs, whereas X represents the parameter value to be normalized. Xmin refers to the minimum value of a parameter, while Xmax represents the highest value of a parameter. The formula in this context yields CSSR parameters bounded from 0 to 1. The reference data normalized using the provided formula will be utilized as the reference data during testing with the Euclidean distance parameter. The hamming distance parameter involves converting the normalized reference data into binary form using specified limitations for each CSSR parameter. Consequently, the converted binary form only consists of two values, namely 0 and 1. Upon data preservation, the optimization of CSSR will be conducted utilizing actual data from the CSSR test data, employing the reference data.

2.3 CSSR Optimization Using Real Data

The optimization stage of CSSR involves the utilization of actual data. During this stage, CSSR input data obtained from the Servo Analytic program is tested using the k-NN algorithm. This involves the computation of the shortest distance between the test data and the reference data. To do this, the distance and k value parameters are initially determined. To begin, choosing the specific Base Transceiver Station (BTS) for which the Call Setup Success Rate (CSSR) data will be evaluated is necessary. Once the BTS has been selected, the next step is to choose the appropriate reference data from the aforementioned BTS. Next, choose the input Common Subsystem Radio (CSSR) data from the designated Base Transceiver Station (BTS). Subsequently, the distance parameter and the parameter value k should be chosen as guiding factors in the computation of the minimum distance between the reference data and the CSSR test data. The selection of the Euclidean distance metric is based on the normalized reference data. On the other hand, the selection of reference data for the Hamming distance parameter is made in binary form. The parameter value, denoted as k, exhibits a count value range

from 1 to 15. During the testing phase, several key components are required, including reference data, test data, optimization target class, distance parameter, and k value

parameter. Once all of the specified parameters have been satisfied, the process of k-NN testing can be initiated. Once the CSSR input data has undergone testing using the k-NN algorithm, it will be possible to determine the success rate of k-NN in generating CSSR optimization recommendations that align with those made by an engineer.

2.4 CSSR Optimization Using Simulation Data

The CSSR optimization stage using simulation data is the stage where k-NN is able to provide CSSR optimization decisions on new CSSR data (simulation data). The stages are almost identical to the CSSR optimization stage using real data. The difference is the test data used. At this prediction stage, the system must fill out with new CSSR data values online or directly. Input data with entered values will automatically form a 1x8 matrix used as test data. Reference data for this prediction stage have been determined for each BTS area, such as urban, dense urban, and suburban. By selecting an existing BTS area, it will also automatically select reference data and optimization target classes according to the selected BTS area. Then, the distance and k-value parameters are determined to calculate the shortest distance between the new CSSR data and the predetermined reference data. At this stage, reference data, new test data (simulation data), optimization target class, distance parameter, and k value parameter are needed. If all of these parameters have been met, then the decision to optimize CSSR using k-NN can occur.

3. Result and Discussion

3.1 Formation of Reference Data

The Call Setup Success Rate (CSSR) performance data used as reference data is 15 CSSR data from 5 days of CSSR data collection for each BTS because, in 1 day, there are three sectors or 3 CSSR data in each BTS. At BTS Unnes Sekaran on January 7, 2013, January 17, 2013, and March 3-5, 2013, DCS Salatiga on January 6-8, 2013, January 14, 2013, and January 18, 2013, which totalled 30 data. The reference data is formed based on the general problems in each BTS, which can be seen from the optimization targets or optimization decisions by operators (engineers) in the field. CSSR data not used as reference data will become test data when testing CSSR optimization using real data.

3.2 Proposed specifications

The Call Setup Success Rate (CSSR) performance data used as test data for CSSR optimization uses 255 real data for each BTS so that the total test data for all existing BTS is 2 x 255 = 510 CSSR data. Optimization is carried out by providing variations in the distance and k-value parameters. From the results of testing the test data, it can be seen that the percentage of success of k-NN in providing optimization decisions is in accordance with the optimization target. The following is the percentage formula for the success of CSSR optimization on formula 2.

$$\%\ Opmtimization = \frac{\text{The number of decisions that match the target}}{\text{Total all test data}}\ x\ 100\% \quad (2)$$

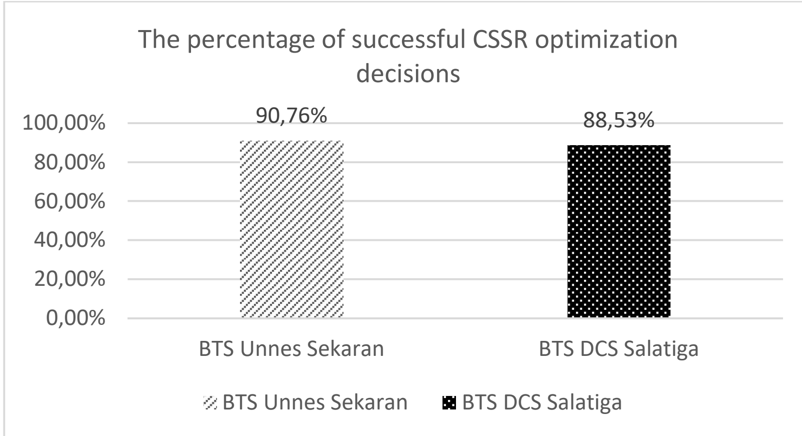

Figure 2. Graph of the percentage of success in optimizing CSSR real data for each BTS

of 90,76%, and the lowest percentage of success in optimizing CSSR is in BTS DCS Salatiga, with a success percentage of 88,53%. But overall, the percentage of success in optimizing CSSR for all test data is 89,65%. Compared with the Artificial Neural Network (ANN) method used to optimize CSSR data in previous studies, the percentage of successful Optimization of CSSR for all test data was 90.56% [6]. There is a difference in the percentage of success between the k-NN and ANN methods because, in ANN, there is a training process before entering the testing process. Hence, each CSSR parameter in ANN has a different weight, whereas in k-NN.

3.3 Effect of Distance Parameter Selection

This part aims to investigate the impact of the distance parameter on the success rate of CSSR optimization. The distance parameter determines the most efficient approach to measuring the shortest distance between reference data and test data in optimizing CSSR actual data. This is achieved by utilizing two specific parameters, namely the Euclidean and Hamming distance.

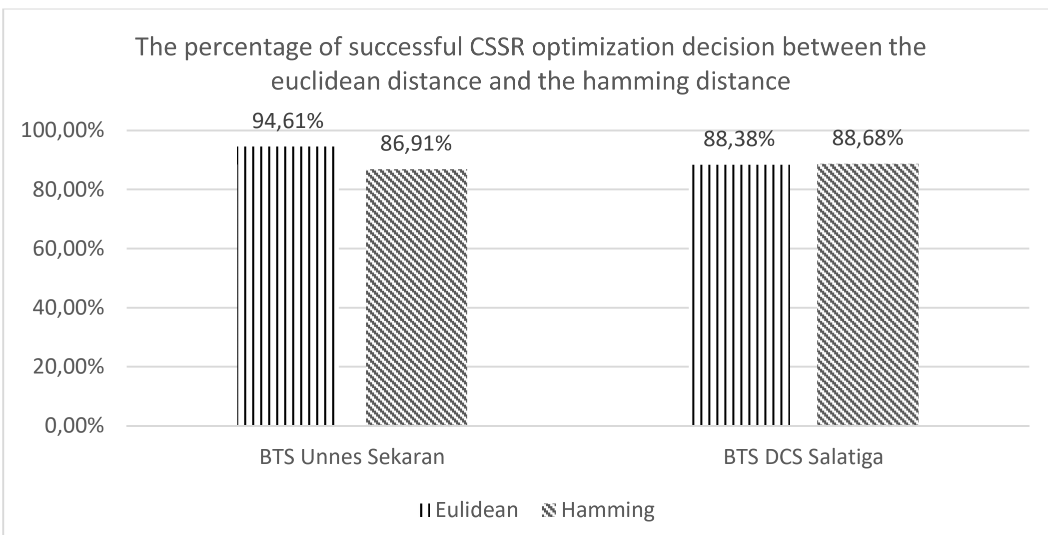

Figure 3. Graph of the percentage of CSSR Optimization success for real data on each distance parameter

Figure 3. shows that the percentage of success using the Hamming distance is greater than the percentage of success using the Euclidean distance. At the Hamming distance, it has a success percentage of 87,79%, and at the Euclidean distance, it has a success percentage of 91,49%. This happens because, at the hamming distance, all CSSR parameter values only have two values (binary), namely 0 and 1. If the value of a CSSR parameter is 0, then it has a low value, and if the value of a CSSR parameter is 1, it has a high value. In determining the high and low values of a CSSR parameter, certain value limits are required so that the various parameter values are only 2.

3.4 Effect of Selection Parameter Value of K

This study aims to investigate the impact of the k-value parameter on the success rate of CSSR optimization in a controlled experiment. The k value represents the quantity of nearest neighbours and is afterwards employed to ascertain CSSR optimization choices. In order to do the tests, the values of k that have been selected are 1, 3, 5, 7, 9, 11, 13, and 15. The influence of the value of k on the amount of success in determining CSSR optimization decisions is evident in Figure 4. The success rate percentage exhibits variability in relation to the input k-value without displaying any discernible trend of either decline or rise with changes in the k-value. The highest levels of success are observed at k = 3 and k = 5, with success rates of 92.95% for both values. The success rate is less than 90% when the value of k exceeds 5. This phenomenon occurs due to the fact that the majority of reference data exhibits characteristics that are optimized towards a goal value of 1, which is considered normal. The majority of CSSR data that has been tested is optimized to achieve a target value of 1, which is considered normal. With a higher value of k, the number of voting possibilities to decide the nearest neighbors will be minimized. The act of voting is a decision-making process that may not always yield entirely accurate outcomes.

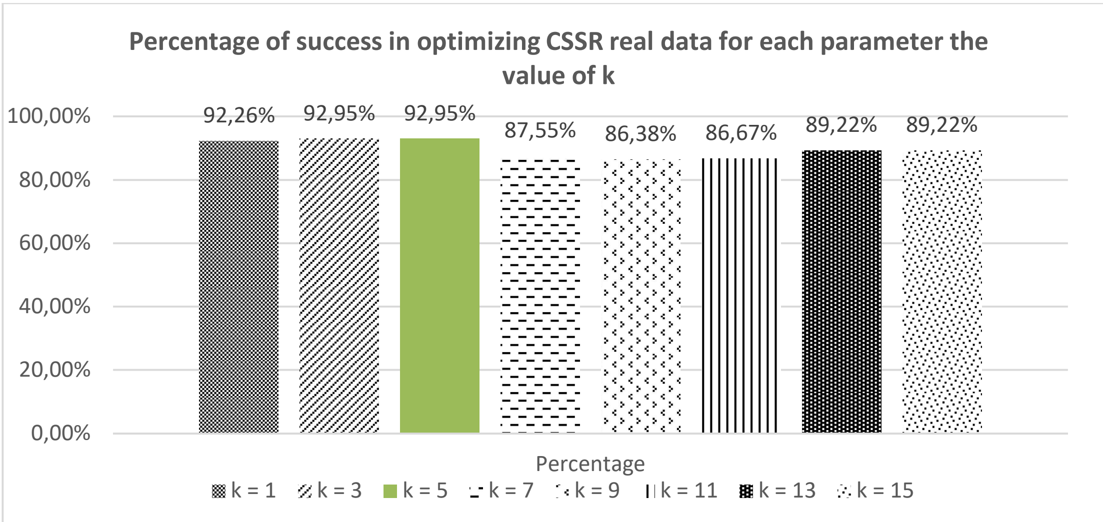

Figure 4. Graph of the percentage of success in optimizing CSSR real data for each parameter the value of k

3.5 CSSR Optimization Using Simulation Data

Improving Call Setup Success Rate (CSSR) performance data involves utilizing simulation data acquired by manual input of CSSR parameter values within a predetermined range of parameter values. The optimization of CSSR is performed considering the geographical location or coverage area of the Base Transceiver Station (BTS). BTS is situated in three distinct geographical settings, specifically metropolitan areas, densely populated urban areas, and suburban areas. The distance metrics employed for optimization using simulation data consist of Euclidean and Hamming distance. Additionally, the values of k utilized in the analysis are k=1, k=3, and k=5. The CSSR parameters and their corresponding optimization decisions are presented in Tables 1, 2, and 3. When the optimization decision equals 1, the corresponding optimization is called 'Normal.' When the optimization decision equals 2, the corresponding optimization is called 'TCH Addition.' When the optimization decision equals 3, the corresponding optimization is called 'SDCCH Addition.' In the event that the optimization decision is determined to be 4, it can be concluded that the corresponding optimization name is 'HCR.'

TABLE 1 OPTIMIZATION OF CSSR USING SIMULATION DATA ON BTS URBAN AREAS

CSSR Parameter	**Data 4**	**Data 3**	**Data 2**	**Data 1**
Total Traffic (Erlang)	800	600	633,1	650
Call Attempt (Panggilan)	27000	17000	16023	17560
BH TCH (Erlang)	58	28,3	50	51,89
Max Available CS (Circuit switch)	47	26	28	30
Availability of TCH (%)	100	100	99,98	100
Drop Rate of SDCCH (%)	4	3,7	0,09	0,07
Block Rate of SDCCH (%)	8,7	0,01	0,01	0,009
TCH Block Rate (%)	12,67	0,45	7,02	0,43
Optimization Decision Using Hamming Distance	K equals 1	K equals 1	K equals 1	K equals 1
	K equals 3	K equals 3	K equals 3	K equals 3
	K equals 5	K equals 5	K equals 5	K equals 5
Optimization Decision Using Euclidean Distance	K equals 1	K equals 1	K equals 1	K equals 1
	K equals 3	K equals 3	K equals 3	K equals 3
	K equals 5	K equals 5	K equals 5	K equals 5

TABLE 2 OPTIMIZATION OF CSSR USING SIMULATION DATA ON BTS IN DENSE URBAN AREAS

CSSR Parameter	Data 4	Data 3	Data 2	Data 1
Total Traffic (Erlang)	741	704	724	220
Call Attempt (Panggilan)	28118	20118	20124	13823
BH TCH (Erlang)	23,56	24,26	24,23	17,23
Max Available CS (Circuit switch)	27	31	31	30
Availability of TCH (%)	100	99.7	99,98	99.99
Drop Rate of SDCCH (%)	3,89	0,1	0,1	0.04
Block Rate of SDCCH (%)	8,03	4,03	0,03	0.007
Block Rate of TCH (%)	7,94	0,2	4,7	0
Optimization Decision Using Hamming Distance	K equals 1	K equals 1	K equals 1	K equals 1
	K equals 3	K equals 3	K equals 3	K equals 3
	K equals 5	K equals 5	K equals 5	K equals 5
Optimization Decision Using Euclidean Distance	K equals 1	K equals 1	K equals 1	K equals 1
	K equals 3	K equals 3	K equals 3	K equals 3
	K equals 5	K equals 5	K equals 5	K equals 5

TABLE 2 OPTIMIZATION OF CSSR USING SIMULATION DATA ON BTS IN SUB-URBAN AREAS

Parameter CSSR	Value 4	Value 3	Value 2	Velue 1
Total Traffic (Erlang)	2,37	195,5	230,5	227,3
Call Attempt (Panggilan)	69	7820	4280	6790
BH TCH (Erlang)	0,54	14,74	12,29	21,59
Max Available CS (Circuit switch)	38	38	35	34
Availability of TCH (%)	100	100	100	100
Drop Rate of SDCCH (%)	0,03	0,03	0,03	0,06
Parameter CSSR	Nilai 4	Nilai 3	Nilai 2	Nilai 1
Block Rate of SDCCH (%)	6,57	0,57	0,009	0
Block Rate of TCH (%)	5,01	0,01	3,38	0
Optimization Decision Using Hamming Distance	K equals 1	K equals 1	K equals 1	K equals 1
	K equals 3	K equals 3	K equals 3	K equals 3
	K equals 5	K equals 5	K equals 5	K equals 5
Optimization Decision Using Euclidean Distance	K equals 1	K equals 1	K equals 1	K equals 1
	K equals 3	K equals 3	K equals 3	K equals 3
	K equals 5	K equals 5	K equals 5	K equals 5

5. Conclusion

The highest percentage of success in optimizing CSSR using real data is the highest in CSSR data found in BTS Unnes Sekaran at 90.76% and the lowest in BTS DCS Salatiga at 88.53%. Overall, the percentage of successful CSSR optimization using real data on all CSSR data can be considered excellent because it has a success percentage of 89.65%. The percentage of successful optimization of CSSR using real data using the Euclidean distance parameter is 91.49%, and the percentage of successful optimization of CSSR using real data using the hamming distance parameter is 87.79%. The percentage of successful CSSR optimization using real data fluctuates depending on the number of nearest neighbors (k value) used. There is no tendency to decrease or increase as the value of k changes. A high percentage of success is at k = 3 and k = 5, with each value of 92.95%. The percentage of success when the number k > 5 is below 90%. This happens because most of the reference data that is made has characteristics that have an optimization target of 1 (Normal). Most CSSR data tested also has an optimization target of 1 (Normal). So, with a large value of k, it will minimize the voting opportunities to determine the nearest neighbors Voting itself is a decision-making method whose results are not necessarily completely correct. The advice that can be given in relation to the implementation of this research is that this research can be developed to optimize the performance of the Call Setup Success Rate (CSSR) in data services by using a larger number of BTS parameter data samples. In addition, it can also be developed to optimize the performance of the Handover Successful Rate (HOSR) and Call Drop Rate (CDR) on cellular operators.

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