Decision Optimization: Internet Data Assistance for Students during Learning from Home

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Abstract: ***The teaching and learning process during the Covid-19 pandemic made it difficult for students to provide internet data packages for access online learning media from home. An internet assistance program policy is provided to support student online learning. In order for the distribution of internet data to students is objective and proportion, for that reason, measuring the amount of data usage and then used in decision making. The method used in measuring data usage is the Drive-test method for incoming and outgoing data bandwidth. As for the analysis of data assistance decision making using the optimization method and the Rank Order Cendroid (ROC) weighting method for each criterion. Measurement results of internet data usage obtained an average value of 407MB-1.0GB per hour with 40 participants in the group. The results of the decision making analysis method for internet data assistance obtained the highest optimization value obtained by 0.40117 with a weighted ROD value of 0.4667. The research study on internet data usage and optimization of decision-making methods is a case study in the Computing classification field: networks and applied computing. Both are implemented in management optimization internet data assistance to students.***

Keywords **:** ***data usage, learning from home, decision, students.***

I. INTRODUCTION

In an effort to prevent the Covid-19 pandemic, the Indonesian government issued a policy of changing the conventional learning system from schools to online learning[1]. Cause major changes in the learning process. The most visible impact of changes in the world of education during the Covid-19 pandemic is the effectiveness of the teaching and learning process. The reason is, not all students are able to adapt to this new learning method (The concept of home-schooling has not yet become mainstream in the discourse of national education in Indonesia). Although they are required to be able to adapt to online learning systems. However, not a few students, parents and educators still find this difficult. Moreover, in terms of providing learning tools, such as internet data packages, internet networks and laptops to support the learning process. According to Media Indonesia website[2], the online learning system which is now causing changes in education in the midst of the Covid-19 pandemic has the potential to create socio-economic disparities, because more than 2 million workers have already been laid off. Under these conditions, many parents find it difficult to provide optimal educational opportunities for their children. In a worse situation, parents may even face a dilemma of choice: feed the family or pay for children's education. The Covid-19 pandemic has had a significant impact on the entire community, therefore, One of the efforts to overcome the cost problem of online learning needs is to provide internet data package assistance to students. This assistance program is generally implemented in several regions of Indonesia through local government policies and educational institutions that distribute internet data packages to support online learning. New problems arise in this assistance program related to equity and objectivity in distribution to target beneficiaries. The proportion of internet data sharing that is considered less effective and efficient, considering the needs of each student are different from others, differences in a load of lessons or courses, the economic ability of students, meeting duration and others. The research objective proposes a multi-objective decision-making method to optimize the distribution of internet data assistance to students, based on the criteria for online learning data needs. The study methodology is divided into 2 parts;

First, field observations, through measurements to determine the amount of data usage per student, per meeting, and per course during the online learning process.

Second, the use of the next measurement result data is the basic criterion for analysis of multi-objective decision making to optimize the distribution of internet data assistance to students. Contribution: (1) The results of measuring the use of internet data in online learning for knowledge information on the amount of data consumption in video communication apps. (2) Decision-making Analysis methods can be a management approach for policymakers in optimization assistance programs are right on the target, proportion and objective.

Revised Manuscript Received on September 30, 2020.
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II. MATERIALS AND METHODS

A. Internet Performance during Covid-19 Pandemic

Telecommunication operator research reveals that internet use has increased during the Covid-19 pandemic worldwide[3].

This condition is in line with the existence of physical distancing policies or even a total lockdown implemented by several countries.

The community works, studies and worships from home. So that the need for the internet also continues to increase.

In Indonesia, since the government appealed to the public to implement leaarning or work from home (L/WFH) as a preventive measure for the spread of the Covid-19 outbreak, there has been a significant increase in internet data usage, Various video conferencing services such as Zoom, CISCO Webex Meetings, or Google Hangouts Meet, immediately became popular as support for online meetings.

Meanwhile, some internal data from Indonesian telecommunication operators shows that their accumulated percentage of broadband services reaches 16% during WFH, and information concerning the initial conditions of the network before the Covid-19 pandemic at the research location, seen in the author's previous study in[4], [5],[6].

The traffic spike was dominated by the growth of online learning application users such as Ruangguru, Ilmupedia Package, and Google Classroom, which increased by more than 5404%.

In addition, there is an increase in users of supporting application services to work from home, i.e video conferencing services such as Zoom cloud meetings, Microsoft Teams, and CloudX by more than 443%.

The most popular application service used by educational institutions in online learning is Zoom.

In this study, the measurements focused on the use of the Zoom cloud meetings application data which is currently still used during the learning from home (LFH).

B. Measurement Methodology

Measurement of internet data usage uses the Drivetest method step approach[7], to collect data usage information in the Zoom cloud meetings app during online learning. Data measurement from the viewpoint of user perception, which assesses the quality of service experience (QoSE)[8],[9] of the amount of data consumption of communication video.

In QoSE measurement, there are many factors that can affect the results of data measurement, in particular on mobile broadband services[10].

For this reason, data collection focuses on visible (measured) and readable (recorded) values in the tools used.

1) Equipment and tools

Equipment and tools used in data measurement are presented in "Table-I".

Table- I: Equipment and tools

Equipment/tools		Decriptions
Software:	Zoom cloud Meetings[11]	Current Version: 5.2.42588.0803, H.323/SIP room systems
	GlassWire data monitoring[12]	Current Version: 3.0.354r
Hardware:	PC or Laptop	2.5 GHz Dual Core Intel Core i5
	Android Tablet	Android OS: Android 4.0 and above Screen size: 8.0 inch

2) Measuring parameters

The parameters measured are the metric of internet network application performance on the value of data usage. which is presented in "Table-II".

Table- II: Measuring parameters

Metric parameters		Decriptions
Data usage	Incoming data	Traffic is received as it is coming into the computer (streaming video)
	Outgoing data	Traffic is sent/transmitted as it is going out from this computer (requests data) in MB
duration	60 minutes	Duration of meetings learning per course

C. Decision Analysis Methods

Decision analysis, which has been very popular in use during the last few decades, is known as Multi-criteria Decision Analysis (MCDA). The role of MCDA in the different areas of implementation has increased significantly especially as new methods develop and old methods increase. In practice, MCDA is concerned with evaluating a set of possible actions or options and this evaluation can be in the form of selecting the preferred option, classifying the options from best to worst [13]. In practice, Implementation of Multi-criteria Decision Analysis is very important in allocating limited resources between alternatives and competing interests[14].

The multi-attribute decision-making method (MADM) was designed for problems with a predefined set of alternatives, whereas the multi-objective decision-making method (MODM) is for problems where the alternative set is not predetermined[15]. The terms MADM and MCDA (or MCDM) are sometimes used interchangeably in the literature[16],[17] which can cause some confusion as stated. Another classification for the MCDA method is proposed by Belton et al.[18] which is divided into three types, i.e. Value measurement models; Objective, aspiration or reference level models; and outranking model. By combining this preference information into all relevant criteria, the model seeks to build the strength of the evidence supporting the selection of one alternative over another (Mendoza & Martins, 2006)[19]. As stated by Govindan et al. (2016)[20], the number of literature reviews on the most popular MCDA methods has grown.

Among the growing variety of MCDA methods, In the case of optimizing the distribution of internet data assistance to students, the Multi-Objective Optimization decision analysis approach on The Basic of Ratio Analysis is used. The method has a degree of flexibility and understandability in separating the subjective part of an evaluation process into decision-weight criteria with several attributes of decision making [21],[22] Method has a good level of selectivity because it can determine the objectives of conflicting criteria-attribute[23]. Where the criteria can be valued for a benefit (max) or cost (min).

The analysis approach of multi-objective optimization (Normalized Decision Matrix, Reference Points, Assessment Values, and final Ranking of Alternatives) for internet data assistance programs refers to[24], [25], [26] :

The Normalized Decision Matrix of "(1)"[25]:

$$r_{ij}^{*} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^{2}}}; \text{j = 1, …,n} \qquad (1)$$

Where, xij: Alternative matrix j on criterion i,
i: 1,2,3, ..., n = the sequence number of the attribute
h: 1,2,3, ..., m the alternate sequence number
X * ij: Alternative j normalization matrix on criterion i

For optimization, these normalized performances are added in the case of maximization (for beneficial attributes) and subtracted in case of minimization [27], in "(2)":

$$y_i = \sum_{j=1}^{g} x_{ij}^* - \sum_{j=g+1}^{n} x_{ij}^* \quad (2)$$

Relates to attribute weights [w1, w2,…,wn], the assessment value of each attribute is obtained using "(3)".

$$\hat{y}_j = \sum_{j=1}^{g} x_{ij}^*.w_j - \sum_{j=g+1}^{n} x_{ij}^*.w_j ;\ i = 1,\ldots,m \quad (3)$$

An order of rank from yi indicates the last choice. Thus, the best alternative has the highest y_i value while the worst alternative has the lowest y_i value.

D. Internet Data Assistance Criteria

The Internet Data Assistance Program for students is a support program that is distributed in the form of internet data packages that are sent to students' telephone numbers every month during Learning from home due to Covid-19. Determination of criteria through field observations (online questionnaire form) to obtain initial information regarding the cost needs, and student characteristics during the LFH Covid-19 pandemic. Decision analysis to determine the amount of data packages use 4 decision-making criteria, the criteria are shown in "Table- III".

Table- III: Criteria for internet data assistance.

code	Criteria	Decriptions
C1	Internet data usage	Internet data needs (Usage) of students from the measurement results (MB) per meeting
C2	Number of courses	The number of student courses taken per semester (theory or practice)
C3	Data quota purchasing power	Budget for student data quota purchases from their parents per month (IDR)
C4	Academic credits	Number of academic credits taken per semester (1 credit = 45 - 60 minutes practice)
C5	Monthly cost	The amount of subsidies costs from parents to students per month (IDR)

Determination of weighting for the crisp value uses a fuzzy set. Fuzzy metrics (crisp) are Internet data usage, low; medium; hight and very-high.

Table- IV: The criteria, crisp and weight values

Code	Criteria	Crisp	Set	Max/Min
C1	Internet data usage (MB)	400 - 559 560 - 749 750 - 909 910 - 1060	1 2 3 4	Max
C2	Number of courses	5 6 7 8	1 2 3 4	Max
C3	Data quota purchasing power (IDR)	100.000-175.000 176.000-250.000 251.000-325.000 326.000-400.000	1 2 3 4	Min
C4	Academic credits	14 – 16 17 – 19 20 – 22 23 – 24	1 2 3 4	Max
C5	Monthly cost (IDR)	1.000.000-1.750.000	1 2	Min
		1.760.000-2.500.000 2.510.000-3.250.000 3.260.000-4.000.000	3 4	

III. RESULTS

Presentation of measurement internet data assistance divided into 3 parts, i.e. Descriptive characteristics of participant samples, measurement of internet data usage, and the optimization of decision making for internet data assistance.

A. Descriptive characteristics of participant samples

This section, we present descriptive characteristics of participants who were sampled for measurement of internet data usage, for potential beneficiaries and in various sections of the study. The sampling method used was a purposive sampling models, in which, determining the sample that was useful in the research objectives, i.e. students who were the target potential beneficiaries of internet data assistance, and those who are carrying out online learning activities during the Learning from Home Pandemic Covid-19 policy. The number of samples is presented in "Table V".

Table- V: Descriptive characteristics for sample

Students academic year		Number of courses	Students	Gender	
				Male	Female
1st	Classroom A	8	40	27	13
2nd	Classroom B	7	40	22	18
3rd	Classroom C	6	40	27	13
4th	Classroom D	5	40	28	12
		Total	160	104	56

B. Measurement results: internet data usage

The data measurement results per student academic years. Statistical description of the measurement data usage, shown in "Table VI" and Barchart in "Fig. 1".

Table- VI: Descriptive characteristics data usage

N = 160	Incoming Data	Outgoing Data	Total Data Usage
Mean	389.9408	231.9383	621.8793
Median	360.3400	213.7200	595.0950
Mode	214.66	107.07	407.92
Std. Dev	124.29899	84.74490	131.64042
Variance	15450.239	7181.697	17329.201
Range	496.68	384.91	599.35
Minimum	214.66	107.07	407.92
Maximum	711.34	491.98	1007.27
Sum	62390.52	37110.12	99500.69

The results of the measurement of data usage ("Table VII and "Fig.1"") showed that the average incoming value was 367.76MB and outgoing 238.06MB. Thus, the average total value is 605.81MB. Furthermore, the minimum average value of the total data usage is 416.70, and the maximum value is 913.97MB.

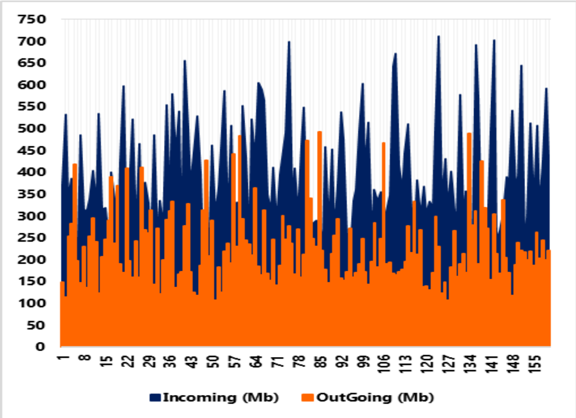

Fig. 1.The barchart data usage

Table- VII: Measurement results for data usage

Student	Incoming (MB)	Outgoing (MB)	Total (MB)
A1	373.27	148.37	521.64
A2	532.74	114.44	647.18
A3	340.89	254.62	595.51
A4	385.66	283	668.66
A5	235.68	418.93	654.61
A↓..	⋮	⋮	....
A41	656.31	277.76	934.07
A42	499.93	328.66	828.59
A43	363.96	172.71	536.67
A44	446.72	125.6	572.32
A↓..	⋮	⋮	....
A81	289.22	472.54	761.76
A82	224.14	340.46	564.60
A83	283.33	248.35	531.68
A84	290.77	231.3	522.07
A↓..	⋮	⋮	....
A121	333.29	129.96	463.25
A122	317.99	170.04	488.03
A123	494.29	299.36	793.65
A124	711.34	230.13	941.47
A↓..	⋮	⋮	....
A156	507.15	262.4	769.55
A157	310.67	203.9	514.57
A158	426.89	245	671.89
A159	592.18	200.1	792.28
A160	430.93	221.9	652.83
Avg.	**389.9408**	**231.9383**	**621.8793**
Min.	**214.66**	**107.07**	**407.92**
Max.	**711.34**	**491.98**	**1007.27**

The measurement results obtained, tabulated data based on the interval value (crisp) for the criteria internet data usage ("Table 3"), then, crisp value is obtained as shown in "Fig 2".

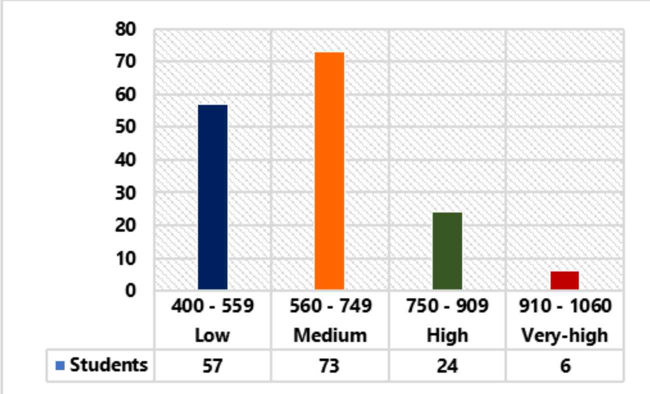

Fig. 2. Interval value for the internet data usage

The final tabulation of measurements that combines the average values of incoming, outgoing and total data for each class ("Table VII"). Thus, the average data usage value is 389.94MB for incoming, 231.94MB for outgoing, and a total average of 621.88MB for 60 minutes of meeting duration, or 10,364MB of data per minute.

C. Optimization: DM - Internet Data Assistance

Description statistics for criteria internet data assistance are presented in "Table VIII".

Table VIII: Description statistics for criteria data

Stat.	Internet data (C1)	Courses (C2)	Data quota PP (C3)	Credits (C4)	Monthly cost (C5)
Mean	621.88	6.50	237,500	20.39	2,089,062.5
Median	595.10	6.50	225,000	21.00	2,000,000
Mode	407.92	5.00	125,000	24.00	1,500,000
Std.	131.64	1.12	78,106.5	3.47	805,516.98
Min	407.92	5.00	125,000	14.00	1,000,000
Max	1,007.2	8.00	375,000	24.00	3,750,000

1) Decision matrix making

Initial decision-making matrix of 160 students, shown in "Table IX":

Table IX: Initial decision-making(DM) matrix

Alt. ↓	(C1)	(C2)	(C3)	(C4)	C5)
A1	521.64	8	375,000	24	3,000,000
A2	647.18	8	300,000	24	2,500,000
A3	595.51	8	275,000	24	1,000,000
A↓	⋮	⋮	⋮	⋮	⋮
A51	407.92	7	125,000	23	1,000,000
A52	551.14	7	375,000	16	3,000,000
A↓	⋮	⋮	⋮	⋮	⋮
A91	667.57	6	200,000	17	1,750,000
A92	696.41	6	250,000	24	2,000,000
A↓	⋮	⋮	⋮	⋮	⋮
A159	792.28	5	300,000	22	1,750,000
A160	652.83	5	225,000	14	2,250,000

The initial data in "Table IX" are normalized (fuzzy set) which assigns a value (weight) to each criterion.

Four categories, i.e. Low = 1, Medium = 2, High = 3, and Very-high = 4. The set values are presented in "Table X".

Retrieval Number: 100.1/ijitee.K78450991120
DOI: 10.35940/ijitee.K7845.0991120
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication

Table X: Initial DM-matrix with set value (weight)

Alt. ↓	(C1)	(C2)	(C3)	(C4)	(C5)
A1	1	4	4	4	3
A2	2	4	3	4	3
A3	2	4	3	4	1
A↓	⋮	⋮	⋮	⋮	⋮
A51	1	3	1	4	1
A52	1	3	4	1	3
A↓	⋮	⋮	⋮	⋮	⋮
A91	2	2	2	2	2
A92	2	2	2	4	2
A↓	⋮	⋮	⋮	⋮	⋮
A159	3	1	3	4	2
A160	2	1	2	1	2

Based on the values in "Table X", the decision matrix data (X) is obtained as follows:

$$X = \begin{bmatrix} 1 & 4 & 4 & 4 & 3 \\ 2 & 4 & 3 & 4 & 3 \\ 2 & 4 & 3 & 4 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 3 & 1 & 4 & 1 \\ 1 & 3 & 4 & 1 & 2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 2 & 2 & 2 & 2 & 2 \\ 2 & 2 & 2 & 4 & 2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 3 & 1 & 3 & 4 & 2 \\ 2 & 1 & 2 & 1 & 2 \end{bmatrix}$$

2) Normalization matrix

Making Normalization Matrix according to "(1)", is to determine the normalized value for each criterion of each alternative and make it a normalized matrix. The calculation results for each criterion and alternative (normalization matrix) are as follows:

$$X^* = \begin{bmatrix} 0.039 & 0.462 & 0.522 & 0.409 & 0.304 \\ 0.156 & 0.462 & 0.294 & 0.409 & 0.304 \\ 0.156 & 0.462 & 0.294 & 0.409 & 0.304 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0.039 & 0.260 & 0.033 & 0.409 & 0.304 \\ 0.039 & 0.260 & 0.522 & 0.026 & 0.304 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0.156 & 0.115 & 0.131 & 0.102 & 0.135 \\ 0.156 & 0.115 & 0.131 & 0.409 & 0.135 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0.350 & 0.029 & 0.294 & 0.409 & 0.135 \\ 0.156 & 0.029 & 0.131 & 0.0261 & 0.135 \end{bmatrix}$$

3) Optimization Value Calculation

The calculation of the Multi-objective Optimization Value (max-min) in this case refers to "(3)" because each criterion has its own weight (W).

In determining the weight of the criteria, we use the Rank Order Cendroid (ROC) approach which refers to [28], [29]. The weighted value for each criterion is shown in "Table XI".

Table XI: The weighting criterion using ROC

Criterion	Weight $w_i = \frac{1}{n}\sum_{j=1}^{n}\frac{1}{j}, i = 1, 2, .., n$	Rank
Internet data usage (C1)	$w1 = (\frac{1}{5})*(\frac{1}{1} + \frac{1}{2} + \frac{1}{3} + \frac{1}{4} + \frac{1}{5}) = 0.457$	1
Number of courses (C2)	$w1 = (\frac{1}{5})*(\frac{1}{3} + \frac{1}{4} + \frac{1}{5}) = 0.157$	3
Data quota purchasing power (C3)	$w1 = (\frac{1}{5})*(\frac{1}{5}) = 0.040$	5
Academic credits (C4	$w1 = (\frac{1}{5})*(\frac{1}{2} + \frac{1}{3} + \frac{1}{4} + \frac{1}{5}) = 0.257$	2
Monthly cost (C5)	$w1 = (\frac{1}{5})*(\frac{1}{4} + \frac{1}{5}) = 0.090$	4

The optimization value refers to "(3)", is then calculated for each given alternative.

This value refers to "(2)", is the sum of the multiplication of the criterion weight with the maximum attribute value (max), that is, the attribute value of the benefit type (max) is reduced by the multiplication of the criteria weights with the attribute value of the cost (min).

The calculation results are shown in "Table XII".

Table XII: Optimization value (max-min)

Alt. ↓	X1 (max)	X2 (max)	X3 (min)	X4 (max)	X5 (min)	max - min
A1	0.01776	0.07236	0.0208	0.10495	0.02734	0.14686
A2	0.07105	0.07236	0.0117	0.10495	0.02734	0.20928
A3	0.07105	0.07236	0.0117	0.10495	0.00304	0.23358
⋮	⋮	⋮	⋮	⋮	⋮	
A51	0.01776	0.04070	0.0013	0.10495	0.00304	0.15908
A52	0.01776	0.04070	0.0208	0.00656	0.02734	0.01680
⋮	⋮	⋮	⋮	⋮	⋮	
A91	0.07105	0.01809	0.0052	0.02624	0.01215	0.09801
A92	0.07105	0.01809	0.0052	0.10495	0.01215	0.17672
⋮	⋮	⋮	⋮	⋮	⋮	
A159	0.15986	0.00452	0.0117	0.10495	0.01215	0.24544
A160	0.07105	0.00452	0.0052	0.00656	0.01215	0.06476

4) Determination of ranking

The value of Y_i can be positive or negative depending on the maximum total (benefit attribute) in the decision matrix. A ranking order of Y_i denotes the last choice.

Thus the best alternative has the highest yi value while the worst alternative has the lowest Y_i value.

The ranking determination of the optimization value is presented in "Table XIII".

Table XIII: Determination of Rank

Alt. ↓	Optimization value	Rangking
A1	0.14686	72
A2	0.20928	38
A3	0.23358	19
A4	0.24011	16
A5	0.20928	39
⋮	⋮	⋮
A36	0.17888	54
A37	0.40117	1
A38	0.20928	44
⋮	⋮	⋮
A124	0.29094	5
A125	0.03115	150
A126	0.06476	135
⋮	⋮	⋮
A158	0.02831	152
A159	0.24544	15
A160	0.06476	136

From the calculation of the previous Optimization Value ("Table XIII"), the results are sorted from largest to smallest; where the optimization value of the largest alternative is the best alternative from existing data and is the chosen alternative, while the alternative with the lowest optimization value is the worst from the existing data.

In order from largest to smallest, "Table XIV" is shown in the order of ranking 1 – 30.

Table XIV: Ranking

Rangking	Optimization value	Alt. ↓
1	0.40117	A37
2	0.37604	A75
3	0.31981	A35
4	0.29237	A41
7	0.29094	A124
6	0.29094	A136
5	0.29094	A142
8	0.28895	A17
9	0.27683	A21
10	0.26643	A60
11	0.26553	A110
12	0.2573	A50
13	0.2573	A80
14	0.25588	A137
15	0.24544	A159
16	0.24011	A4
17	0.24011	A15
18	0.24011	A28
19	0.23358	A3
20	0.23358	A7
21	0.23265	A81
22	0.23265	A114
23	0.23099	A10
24	0.23099	A18
25	0.23099	A20
26	0.23099	A22
27	0.23099	A26
28	0.22447	A29
29	0.22246	A64
30	0.21908	A123

IV. DISCUSSION

Measurement results in the amount of internet data usage in particular, on the communication video Zoom is affected by many factors such as; network availability issues, communication devices, network technology, application features and others.

In our study, we measured Zoom data usage using a measuring tool to monitor bandwidth usage, incoming and outgoing data. From the measurement results, the average value is lower than Lauren Hannula's[30] measurement, which reveals the zoom usage of around 540MB-1.62GB of data per hour for one-on-one calls, and 810MB-2.4GB per hour for group meetings[30]. Our results obtained 407MB-1.0GB per hour for a meeting with 40 participants in the group, averaging 621.88MB per hour. The presence of a lower value difference is affected by the quality of streaming and usage of the Zoom feature. We see that activities in the presentation of material or media content (data or file types) through sharing screens during online learning, affect the amount of data usage each participant.

Thus, the implementation results of the decision-making method for management of Internet data assistance programs obtained optimal results based on criteria; Internet data usage, number of courses, data quota purchasing power, academic credits and monthly cost student. In the ranking, the highest optimization value is obtained 0.40117. As a method approach to optimize the proportion of acceptance or distribution of internet data packages conforms to student needs in supporting online learning from home during Covid-19 pandemic.

V. CONCLUSIONS

One of the most visible impacts of the changes in the world of education during the Covid-19 pandemic is the effectiveness of the teaching and learning process. The reason is, not all students are able to adapt to this new learning method and the difficulty in providing learning tools, such as internet data packages to support the learning process.

Measurement results of zoom data usage in online learning from home for students, average data usage was obtained value is 389.94MB for incoming, 231.94MB for outgoing, thus an average total of 621.88MB for 60 minutes of meeting duration, or 10,364MB of data per minute. For future research, a study is needed on the effect of using features and content of learning media on data usage. The results of using the optimization method of decision-making analysis for the case of student internet data assistance, obtained a high average optimization value, this is due to the Rank Order Cendroid (ROC) method in weighting the criteria. ROC assigns weight to each criterion according to the ranking that is assessed based on the level of importance or priority, where the highest value is the most important value among the other values. In cases of decision making, the determination of the weighting method is an important factor and has an impact on the optimization results. For this reason, a study of the method of weighting attribute values or criteria in decision making needs further discussion with various decision cases.

ACKNOWLEDGMENT

This research was funded by the Higher Education Institution Operational Assistance Fund (BOPTN), Dept. of informatics, Faculty of engineering, Mulawarman University, Samarinda, east-Kalimantan province, Indonesia.

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