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Implementation of Linear Congruent Methods and Multiplication Random Numbers for Academic Potential Tests

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ABSTRACT

APT (Academic Potential Test) is a test that aims to measure a person's ability in the academic field in general. In the implementation of the APT exam, it is carried out in the admission of new students and its application online, using a website-based application, each prospective new student will be given a login account to take the APT exam simultaneously and at a predetermined time. While the process can be accessed anywhere with an internet network. The implementation of the APT exam does not always run smoothly or well, in fact almost every time the APT exam is carried out there are problems, problems that arise because the questions given do not have differences in workmanship which causes the APT exam results to be impure and accurate. To overcome the problems that continue to occur in the implementation of the APT exam, an algorithm or method is needed that can randomize the questions in the APT exam. In this study, the Linear Congruent (LCM) and Multiplicative Random Number Generator (Multiplicative RNG) methods are random methods that are applied to randomize the APT exam questions so that the APT exam question packages can have different question positions and between question packages and the results of the application of this method will be compared to measures how complex the randomization is for each method. By using the LCM model the level of complexity of the questions increases to 100% while by using the MRNG method the level of complexity of the questions increases to 50%.

Keywords:

Academic Potential Test (APT)
Randomization
Question Package
Linear Congruent Method (LCM)
Multiplicative Random Number Generator Method (MRNG)

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1. INTRODUCTION

APT (Academic Potential Test) is a test that aims to measure a person's ability in the academic field in general. This test is also identified with a person's intelligence test [1]. The questions tested in the academic potential test are identical to the GRE (Graduate Record Examination) test [2]. GRE is a test that also measures a person's ability and talent in academics which is the international standard for student admissions in the United States [3]. In APT there are four areas of ability that are tested, namely: 1. Verbal ability (language) This test aims to test a person's ability in the field of words and language [4]. 2. Numerical ability test (numbers) Is a test that aims to test a person's ability in the field of arithmetic, structured thinking ability to see series of numbers, series of letters [5]. 3. Reasoning ability test (logic) This test tests a person's ability in terms of reasoning and problem solving logically (reasonable) [6]. 4. Spatial ability test (picture) [7]. In the implementation of the APT exam, the application is done online, using a website-based application [8]. Each prospective new student will be given a login account to take the APT exam simultaneously or at a predetermined time, while the process can be accessed anywhere with an internet network. And in the implementation of the APT exam, the questions given here are no different from the process [9].

However, here in the implementation of the APT exam, it does not always run smoothly or well, in fact, almost often in the implementation of the APT exam there are problems, problems that are caused or caused, namely because the questions given are the same. or there is no difference at all in the processing process that creates weaknesses and deficiencies in the process of implementing the APT exam. The problem that often occurs here is that there are many acts of cheating in working on exam questions where the exam can be done together, or every new student candidate can cheat on each other's answers. In the problems that occur, this is not very good because the results obtained or obtained by each prospective new student are not pure or original due to fraud that occurred in the process of implementing the APT exam.

Therefore, to overcome the problems that continue to occur in the implementation of the APT exam, an algorithm or method is needed that can shuffle or scramble the questions in the APT exam so that every prospective new student who takes the APT exam gets results according to their respective answers. with their ability and understanding in answering each question that has been given. Therefore, in overcoming the above problems, a random method is applied that can overcome these problems, namely the Linear Congruent (LCM) method and the Multiplicative Random Number Generator (Multiplicative RNG) [10],[11],[12],[13],[14],[15],[16].

2. RESEARCH METHOD

At this stage describes the stages of research, analysis and testing methods used to obtain comparative analysis results from each pseudo random number generator algorithm. For more details can be seen in Figure 1. as follows:

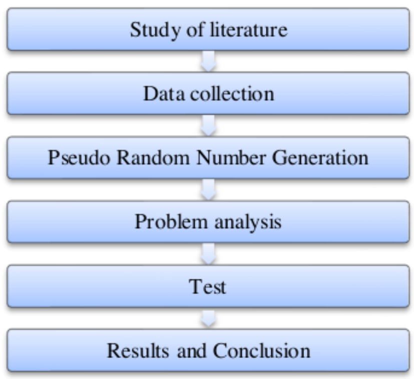

Figure 1. Research Stages

Figure Based on 1 above, it can be explained that the research stages in general are as follows:

1. Study of literature
   At the library research stage, this research uses many library sources, such as books, journals (both printed and online), proceedings, magazines, articles and other relevant sources. This literature is expected to assist researchers in solving problems related to the application of random algorithms in randomizing online APT exam questions.
2. Data Collection
   At this stage the question data taken is data collected as a package of APT Online exam questions.
3. Pseudo Random Number Generation
   At this stage, pseudo random numbers are generated by comparing the Linear Congruent Method (LCM) and Multiplicative Random Number Generator (RNG) algorithms.
4. Problem Analysis
   At this stage the problem analysis aims to randomize the APT Online exam questions and measure the accuracy of pseudo random numbers from the Linear Congruent Method (LCM) and Multiplicative Random Number Generator (RNG) algorithms.
5. Testing
   At this stage, testing is carried out to obtain the validity of the accuracy results that the numbers generated from the results of the Linear Congruent Method (LCM) and Multiplicative Random Number Generator (RNG) algorithms are successfully randomized on the APT Online exam questions.
6. Results and Conclusions

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At this stage, explain the results and conclusions of the validity of the application of the Linear Congruent Method (LCM) and Multiplicative Random Number Generator (RNG) algorithms in randomization and measure the level of accuracy that has been applied to the APT Online exam questions.

a. Linear Congruent Method (LCM) Algorithm

An algorithm is an explanation of the problem solving steps. The following is the algorithm that will be built using the LCM method, which is as follows [17],[18],[19]:

1. Initialize Problem id to Values Xn a, Xn-1, c, and m
2. Input Data and Question ID to Values Xn a, Xn-1, c, and m
3. The Process of Calculation of Randomization Using the LCM Method:

$$X_{n+1} = (aX_{n-1} + c) \text{ Mod } m$$

4. Online APT Question Randomization Process
5. Show APT Question Packages Online

b. Multiplicative Random Number Generator (RNG) Algorithm

Random number algorithm generated by a computer (false random), this random number is generated using a mathematical formula that is repeated as needed. The following is an algorithm that will be built using the Multi RNG method, which is as follows [20],[21],[22]:

1. Initialize the Problem id to Zo, a, c, m
2. Input Data and Question id into Zo, a, c, m
3. The Process of Calculation of Randomization of Questions with the Multi RNG Method:

$$Z_{i+1} = (a \cdot Z_i + c) \text{ mod } m$$
$$R_1 = Z_{i+1} / m$$

4. Online APT Question Randomization Process
5. Appear Ranking With The Lowest R Value

c. System Analysis

The system analysis in this study was carried out by applying the LCM and MRNG methods for randomizing APT Online questions. The key to generating random numbers with LCM and MRNG is Xi-1 which is called the seed. LCM and MRNG have a period not greater than m (modulus), and in this case the period is less than that. LCM and MRNG have full periods if the following conditions are met.

1. Determine the value of the constant C must be greater than the root of m.
2. The value of the constant C cannot be a multiple of m.
3. The value of m must be a prime number.
4. The first value of xn must be greater than 0 and less than the value of m.
5. The constant a must be odd.

And to analyze the system, here using several algorithms with several stages, namely, as follows:

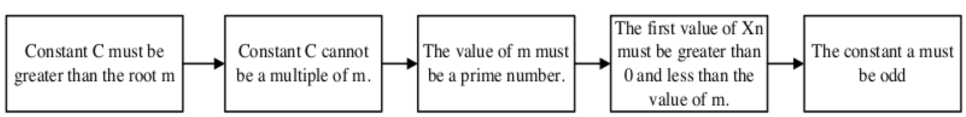

Figure 2. Flowchart of LCM and MRNG

The randomization test aims to calculate an algorithm to find a new package of questions that will be displayed during the APT Online exam. For randomization of questions that will be displayed using the LCM and MRNG methods, it is determined:

1. the value of C = 21, determined from the year the APT Online exam was held and for the C value in the next question package, 2 will be added from the previous C value. The addition of a value of 2 given to the next question package at the value of C serves to form a new random number in the next question package.
2. Constant C cannot be a multiple of the value of m
3. The value of m = 410, is determined from the number of APT Online questions that will be randomized and are prime numbers that are not multiples of the C value.
4. The value of X_n = 60, is determined from the number of questions to be displayed, which is 60 and the value of X_n in the next question package is the same as the value of C which will be added by 2 from

the previous X_n value. The addition of a value of 2 given for the next question package equal to the value of X_n serves to form a new random number in the next question package.

5. The constant a must be odd, so a = 1, determined by the odd value at the beginning of the decimal number.

The randomization process will display 60 questions out of 410 questions for each package, which use the LCM and MRNG methods with the procedure and reference values to form the randomization below:

1. **LCM Procedure :**

Xn+1 = (aXn-1 + c) Mod m

Where :

Xn+1 = nth random number (≥ 0, < m)
a = constant multiplier (a < m)
c = shift constant (c < m)
m = constant modulus (> 0)

2. **MRNG Procedure :**

Zi+1 = (a . Zi + c) mod m

R1 = Zi+1 / m

Where :

Xn+1 = nth random number (≥ 0, < m)
a = constant multiplier (a < m)
c = shift constant (c < m)
m = constant modulus (> 0)
Ri = Final Result of Division of m by Xn+1

From the above procedure, it is known that the reference values for randomization are Xn = 60, C = 21, = 1 and m = 410. To avoid the question code = 0, the calculation results will be added to the number 1.

3. RESULTS AND ANALYSIS

a. LCM Randomization Results

By knowing the value of Xn = 60, the value of C = 21, the value = 1 and the value of m = 410. And to avoid the question code = 0, the calculation results will be added to the number 1, below is a picture of the results of randomization from LCM using a jupyter notebook:

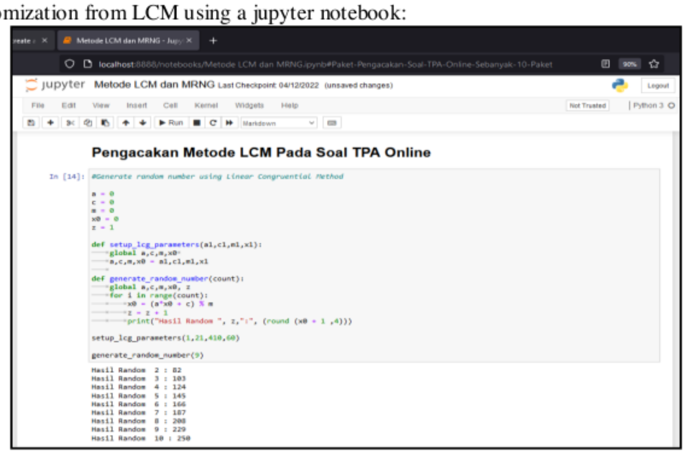

Figure 3. Results of LCM Method Randomization

From the picture above is the result of the calculation of the first package of questions, in this discussion the randomization analysis was carried out as many as 10 question packages consisting of 410 questions and 60 questions that were displayed in each package. Below in Figure 4. you can see the results of the 10 question packages.

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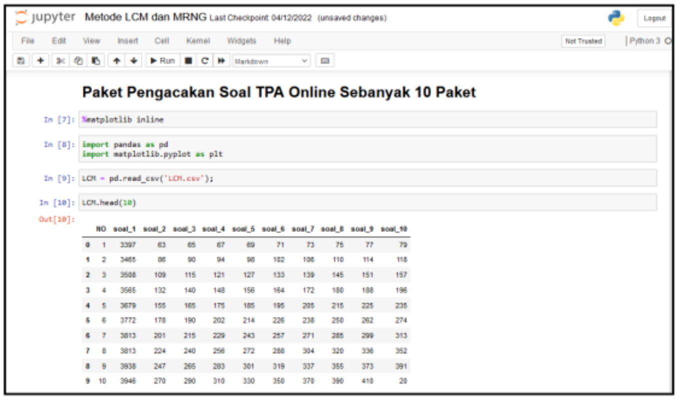

	NO	soal_1	soal_2	soal_3	soal_4	soal_5	soal_6	soal_7	soal_8	soal_9	soal_10
0	1	3397	63	65	67	69	71	73	75	77	79
1	2	3465	86	90	94	98	102	106	110	114	118
2	3	3508	109	115	121	127	133	139	145	151	157
3	4	3565	132	140	148	156	164	172	180	188	196
4	5	3679	155	165	175	185	195	205	215	225	235
5	6	3772	178	190	202	214	226	238	250	262	274
6	7	3813	201	215	229	243	257	271	285	299	313
7	8	3813	224	240	256	272	288	304	320	336	352
8	9	3938	247	265	283	301	319	337	355	373	391
9	10	3946	270	290	310	330	350	370	390	410	20

Figure 4. Results of Question Packages Using LCM 1 – 10

From Figure 4, you can see the results of the Problem Package Using LCM 1 -10, which uses the jupyter notebook application with the python programming language.

b. **MRNG Randomization Results**

In the randomization process, the MRNG method has no difference from the reference for determining randomization with the LCM method, where it is known that the value of Xn = 60, the value of C = 21, the value of = 1 and the value of m = 410. And to avoid the question code = 0 then the results of the calculation will plus the number 1, below is an image of the results of randomization from MRNG using jupyter notebook:


```
#Generate random number using Multivative Random Generator

a = 0
c = 0
m = 0
x0 = 0
z = 1

def setup_lcg_parameters(a1,c1,m1,x1):
    global a,c,m,x0
    a,c,m,x0 = a1,c1,m1,x1

def generate_random_number(count):
    global a,c,m,x0, z
    for i in range(count):
        x0 = (a*x0 + c) % m
        z = z + 1
        print("Hasil Random ", z,":", (x0 +1) / m)

setup_lcg_parameters(1,21,410,60)

generate_random_number(9)
```

```
Hasil Random  2 : 0.2
Hasil Random  3 : 0.25121951219512195
Hasil Random  4 : 0.3024390243902439
Hasil Random  5 : 0.35365853658536583
Hasil Random  6 : 0.40487804878048783
Hasil Random  7 : 0.4560975609756098
Hasil Random  8 : 0.5073170731707317
Hasil Random  9 : 0.5585365853658537
Hasil Random  10 : 0.6097560975609756
```

Figure 5. Results of Randomization of the MRNG Method

From the picture above is the result of the calculation of the first package of questions, in this discussion the randomization analysis was carried out as many as 10 question packages consisting of 410 questions and 60 questions that were displayed in each package. Below in Figure 6 you can see the results of the 10 question packages.

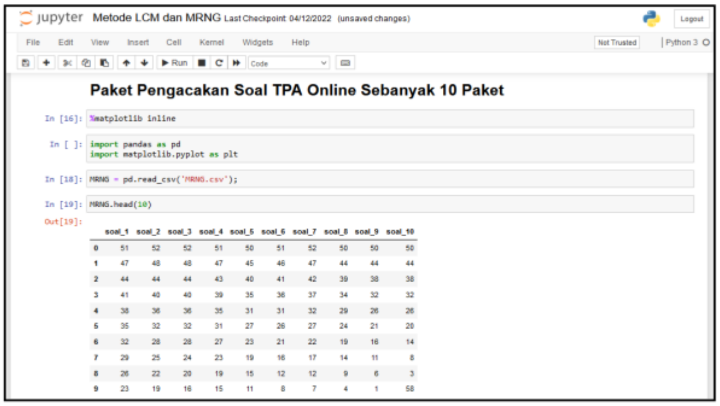

Figure 6. Results of Question Packages Using MRNG 1 -10

From Figure 6, you can see the results of the Problem Package Using MRNG 1 -10, which uses the jupyter notebook application with the python programming language.

c. Analyzing LCM and MRNG Randomization

At this stage one by one clearly shows and analyzes the same questions both from the question package and between the question packages. Below in table 1 can be seen the randomization of the question package.

Table 1 Randomization of Question Packages Using LCM and MRNG

No	*Xn+1 = ((a(Xn + 1)+c)) mod m*	*(Xn +1)*	*Ri = Xn+1 / m*	*Rangking*
1	60	**60** + 1 = **61**	61/410 = **0.1829**	**28**
2	((1*61) + 21) mod 410 = 81	**81** + 1 = **82**	62/410 = **0.2683**	**25**
3	((1*81) + 21) mod 410 = 102	**102** + 1 = **103**	103/410 = **0.3537**	**22**
4	((1*103) + 21) mod 410 = 123	**123** + 1 = **124**	124/410 = **0.4390**	**19**
5	((1*124) + 21) mod 410 = 144	**144** + 1 = **145**	145/410 = **0.5244**	**16**
6	((1*144) + 21) mod 410 = 165	**165** + 1 = **166**	166/410 = **0.6098**	**13**
7	((1*166) + 21) mod 410 = 186	**186** + 1 = **187**	187/410 = **0.6951**	**10**
8	((1*187) + 21) mod 410 = 207	**207** + 1 = **208**	208/410 = **0.7805**	**7**
9	((1*208) + 21) mod 410 = 228	**228** + 1 = **229**	229/410 = **0.8659**	**4**
10	((1*229) + 21) mod 410 = 249	**249** + 1 = **250**	250/410 = **0.9512**	**1**
11	((1*250) + 21) mod 410 = 270	**270** + 1 = **271**	271/410 = **0.0366**	**59**
12	((1*271) + 21) mod 410 = 291	**291** + 1 = **292**	292/410 = **0.1220**	**56**
13	((1*292) + 21) mod 410 = 312	**312** + 1 = **313**	313/410 = **0.2073**	**53**
14	((1*313) + 21) mod 410 = 333	**333** + 1 = **334**	334/410 = **0.2927**	**49**
15	((1*334) + 21) mod 410 = 354	**354** + 1 = **355**	355/410 = **0.3780**	**45**
16	((1*355) + 21) mod 410 = 375	**375** + 1 = **376**	376/410 = **0.4634**	**42**
17	((1*376) + 21) mod 410 = 386	**386** + 1 = **387**	387/410 = **0.5488**	**39**
18	((1*387) + 21) mod 410 = 7	**7** + 1 = **8**	8/410 = **0.6341**	**36**
19	((1*8) + 21) mod 410 = 28	**28** + 1 = **29**	29/410 = **0.7195**	**33**
20	((1*29) + 21) mod 410 = 49	**49** + 1 = **50**	50/410 = **0.8049**	**30**

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21	((1*50) + 21) mod 410 = 70	**70** + 1 = **71**	71/410 = **0.8902**	**27**
22	((1*71) + 21) mod 410 = 91	**91** + 1 = **92**	92/410 = **0.9756**	**24**
23	((1*92) + 21) mod 410 = 112	**112** + 1 = **113**	113/410 = **0.0610**	**21**
24	((1*113) + 21) mod 410 = 133	**133** + 1 = **134**	134/410 = **0.1463**	**18**
25	((1*134) + 21) mod 410 = 154	**154** + 1 = **155**	155/410 = **0.2317**	**15**
26	((1*155) + 21) mod 410 = 175	**175** + 1 = **176**	176/410 = **0.3171**	**12**
27	((1*176) + 21) mod 410 = 196	**196** + 1 = **197**	197/410 = **0.4024**	**28**
28	((1*197) + 21) mod 410 = 217	**217** + 1 = **218**	218/410 = **0.4878**	**25**
29	((1*218) + 21) mod 410 = 238	**238** + 1 = **239**	239/410 = **0.5732**	**22**
30	((1*239) + 21) mod 410 = 259	**259** + 1 = **260**	260/410 = **0.6585**	**19**
31	((1*260) + 21) mod 410 = 280	**280** + 1 = **281**	281/410 = **0.7439**	**16**
32	((1*281) + 21) mod 410 = 301	**301** + 1 = **302**	302/410 = **0.8293**	**13**
33	((1*302) + 21) mod 410 = 322	**322** + 1 = **323**	323/410 = **0.9146**	**10**
34	((1*323) + 21) mod 410 = 343	**343** + 1 = **344**	344/410 = **1.0000**	**7**
35	((1*344) + 21) mod 410 = 364	**364** + 1 = **365**	365/410 = **0.0854**	**4**
43	((1*102) + 21) mod 410 = 122	**122** + 1 = **123**	123/410 = **0.1707**	**1**
44	((1*123) + 21) mod 410 = 143	**143** + 1 = **144**	144/410 = **0.2561**	**59**
45	((1*144) + 21) mod 410 = 164	**164** + 1 = **165**	165/410 = **0.3415**	**56**
46	((1*165) + 21) mod 410 = 185	**185** + 1 = **186**	186/410 = **0.4268**	**53**
47	((1*186) + 21) mod 410 = 206	**206** + 1 = **207**	207/410 = **0.5122**	**49**
48	((1*207) + 21) mod 410 = 227	**227** + 1 = **228**	228/410 = **0.5976**	**45**
49	((1*228) + 21) mod 410 = 248	**248** + 1 = **249**	249/410 = **0.6829**	**42**
50	((1*249) + 21) mod 410 = 269	**269** + 1 = **270**	270/410 = **0.7683**	**39**
51	((1*270) + 21) mod 410 = 290	**290** + 1 = **291**	291/410 = **0.8537**	**36**
52	((1*291) + 21) mod 410 = 311	**311** + 1 = **312**	312/410 = **0.9390**	**33**
53	((1*312) + 21) mod 410 = 332	**332** + 1 = **333**	333/410 = **0.0244**	**30**
54	((1*333) + 21) mod 410 = 353	**353** + 1 = **354**	354/410 = **0.1098**	**9**
55	((1*354) + 21) mod 410 = 374	**374** + 1 = **375**	375/410 = **0.1951**	**6**
56	((1*375) + 21) mod 410 = 395	**395** + 1 = **396**	396/410 = **0.2805**	**3**
57	((1*396) + 21) mod 410 = 6	**6** + 1 = **7**	7/410 = **0.3659**	**61**
58	((1*7) + 21) mod 410 = 27	**27** + 1 = **28**	28/410 = **0.4512**	**58**
59	((1*28) + 21) mod 410 = 48	**48** + 1 = **49**	49/410 = **0.5366**	**55**
60	((1*49) + 21) mod 410 = 69	**69** + 1 = **70**	70/410 = **0.6220**	**51**

In the implementation of the application of the LCM method in the randomization of APT Online questions, there were 10 questions in which 60 questions were displayed out of 410 questions. In the analysis of the question packages above, each package here in the randomization does not have the same questions, both from the question packages and between question packages, which makes this LCM method in terms of randomizing APT Online very good and very feasible to be applied to the APT Online application.

Meanwhile, in the implementation of the application of the MRNG method in the randomization of APT Online questions, there were 10 questions in which 60 questions were displayed out of 410 questions. In the analysis of the package of questions above, there is absolutely no similarity between one question and another, but between the randomization questions there are still many of the same question positions. Below in table 2 can be seen the results of the analysis of the same package of questions between packages. question in question:

Table 2. Same Question Package MRNG

No	Question Package	Initial Question Number	New Question Number	No	Question Package	Initial Question Number	New Question Number
1	1	1	51	**35**	3	6	32
2	4	1	51	**36**	5	6	27
3	6	1	51	**37**	7	6	27
4	2	1	52	**38**	2	7	28
5	3	1	52	**39**	3	7	28
6	7	1	52	**40**	6	9	12
7	5	1	50	**41**	7	9	12
8	8	1	50	**42**	8	17	22
9	9	1	50	**43**	9	17	22
10	10	1	50	**44**	3	30	4
11	1	2	47	**45**	10	30	4
12	4	2	47	**46**	8	30	13
13	7	2	47	**47**	9	30	13
14	2	2	48	**48**	3	35	47
15	3	2	48	**49**	9	35	47
16	8	2	44	**50**	2	48	11
17	9	2	44	**51**	8	48	11
18	10	2	44	**52**	1	51	18
19	1	3	44	**53**	5	51	18
20	2	3	44	**54**	1	52	15
21	3	3	44	**55**	9	52	15
22	9	3	38	**56**	2	52	59
23	10	3	38	**57**	6	52	59
24	2	4	40	**58**	3	52	42
25	3	4	40	**59**	7	52	42
26	9	4	32	**60**	5	53	10
27	10	4	32	**67**	9	53	10
28	2	5	36	**68**	6	53	55
29	3	5	36	**69**	10	53	55
30	5	5	31	**70**	4	59	2
31	6	5	31	**71**	8	59	2
32	9	5	26	**72**	3	60	13
33	10	5	26	**73**	10	60	13
34	2	6	32				

4. CONCLUSION

In the Comparison of the Results of the Application of the LCM Method with the MRNG Method in Randomizing the Online APT Questions, the following will be reviewed from the results to the discussion related to the previous chapter so that it can be seen which one is more superior and feasible between the LCM and MRNG methods in the implementation of online APT randomization.

From the results of the comparative analysis that have been reviewed previously, it can be seen that LCM is clearly superior and good in terms of randomization related to APT Online exam questions because in testing using manual calculations and implementation using Jupyter notebooks the results of the LCM method are very good in terms of packet randomization. and randomization between packages where there is absolutely no similarity in the existing question packages.

Of the 410 randomized questions, 60 questions were displayed for each prospective student which were not sequentially based on the question package. In Table 5.2, a comparison is made between the question packages for prospective students 1 and the question packages for prospective students 10, there are 0 questions that are the same in the question packages for prospective students 1-10, so the percentage level of complexity of the new question packages that have been randomized using the LCM method for each prospective students are:

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$$Question\ Difficulty\ = \frac{number\ of\ questions\ - same\ number\ of\ questions}{number\ of\ models} \times 100\%$$
$$Question\ Difficulty\ = \frac{60-0}{60} \times 100\%$$
$$Question\ Difficulty\ = 100\ \%$$

The MRNG method here is still considered good because in the test using manual calculations and implementation using a Jupyter notebook for randomization of package questions, there is still no similarity in the randomization results. However, here the MRNG method has a problem, namely for randomization between test packages that have been tested by randomizing 1-10 question packages, there are similarities in packages that are repeated with 30 packages of the same questions with the same number. question. In this case it's not very good where randomization doesn't seem to work very well because the results have no difference. Therefore, in the implementation here regarding the Online APT exam, the MRNG method is not recommended to be applied and is related to other cases that apply randomization more than once.

Of the 410 randomized questions, 60 questions were displayed for each prospective student which were not sequentially based on the question package. In Table 2, a comparison is made between the question packages for prospective students 1 and the question packages for prospective students 10, there are 30 similar questions in the question packages for prospective students 1 - 10 which can be seen in table 2 the percentage level of complexity of the new question packages that have been randomized using the method. The MRNG for each prospective student is:

$$Question\ Difficulty\ = \frac{number\ of\ questions\ - same\ number\ of\ questions}{number\ of\ models} \times 100\%$$
$$Question\ Difficulty\ = \frac{60-30}{60} \times 100\%$$
$$Question\ Difficulty\ = 50\ \%$$

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