GAMING LABORATORIES INTERNATIONAL®

GLI®

World Headquarters
600 Airport Road
Lakewood, NJ 08701
Phone (732) 942-3999
Fax (732) 942-0043
www.gaminglabs.com

17 June 2022

Mrs. Pallavi Deshmukh, CEO
NG ENTERTAINMENT US LLC
18 COLUMBIA TURNPIKE, SUITE 200,
FLORHAM PARK, NJ 07932

RE: Random Number Generator Report

File Number: RN-385-NGT-21-01

Dear Mrs. Deshmukh,

Enclosed, please find a detailed explanation of the Random Number Generator (RNG) testing results of the NG Entertainment Limited 'RNG2.0', for use with the "Slots", "Roulette", "Blackjack", and "Keno" games, evaluated against the applicable RNG-specific requirements listed herein.

Please visit Gaminglabs.com to view the applicable Terms and Conditions and GLI Product Certification Scheme.

Registration Number of Accreditation applicable to this Report:	A2LA 2428.05

If you should have any questions regarding this Random Number Generator Report, please feel free to contact our office.

Sincerely,
GAMING LABORATORIES INTERNATIONAL, LLC

Christine M. Gallo
Senior Vice President, Quality and Technical Compliance

djb

Worldwide Locations

World Headquarters
Lakewood, New Jersey

U.S. Regional Offices
Colorado
Nevada

International Offices
GLI Africa
GLI Asia
GLI Australia Pty Ltd
GLI Austria GmbH
GLI Europe BV
GLI Italy
GLI South America

RANDOMNESS REPORT FOR THE RNG2.0 RNG

The intent of this report is to indicate that **Gaming Laboratories International**, **LLC** (GLI) has completed its evaluation of the RNG2.0 random number generator (RNG), provided by NG Entertainment Limited.

SECTION I - SCOPE OF TESTING

GLI was provided the required materials to conduct a randomness evaluation on the RNG2.0 RNG. The scope of this evaluation was limited to software verification, source code review, and statistical testing. The RNG was tested for its ability to randomly produce outcomes for the “Slots’’, ‘’Roulette’’, ‘’Blackjack’’, and ‘’Keno” games.

The RNG2.0 RNG was evaluated against the RNG-specific requirements of the following technical standards:

- Michigan Gaming Control Board - Internet Gaming Rules R432.611 - R432.676
- GLI-19: Interactive Gaming Systems, Version 3.0

SECTION II - SOFTWARE VERIFICATION

Verify+ by Kobetron™ signatures for the RNG2.0 RNG are as follows:

File	Version	Type	Signature
rng_monitor.php	N/A	Kobe4	9116
		MD5	09138683DEC8852A4DDC29A676F288AC
		SHA-1	1E624BA9FC92DA8F3B03FFC13612EBE12AC5E41B
csprng.lib.php	N/A	Kobe4	CA9C
		MD5	0DDFE57734E46BB3DFDCC7A138D4C266
		SHA-1	9C110C5F67D8EA4D998D71D208598831A28C22B4

Table 1. Digital Signatures

SECTION III - SOURCE CODE REVIEW

GLI received the appropriate documentation and FULL source code which pertains to the generation of random numbers. GLI reviewed the source code provided by tracing the path of the RNG application from the initiation of the draw to the selected output of random numbers. GLI inspected the source code, where practicable, in an attempt to find any undisclosed switches or parameters having a possible influence on randomness and fair play. GLI assessed the ability of the RNG to produce all numbers within the desired range.

SECTION IV - STATISTICAL TESTING

The RNG parameters tested are listed in Table 2. GLI performed a data format check on each data set listed in order to confirm that these parameters were correctly represented in the data analyzed.

GLI conducted a statistical analysis of sufficient scope to test the RNG for selecting as many as 20 winners from a pool size as large as 100,000 with replacement and as many as 1,000 winners from a pool size as large as 2,000 without replacement as described in Table 2. The selection of test cases took into account broad coverage of the RNG parameters listed.

A set of numbers is said to be drawn *with replacement* if a number can be selected multiple times within the same draw. A set of numbers is said to be drawn *without replacement* if a number can only be selected once within the same draw.

Data Set	Range	Positions	Replacement
General Testing 1	Up to and including 100,000	Up to and including 20	Yes
General Testing 2	Up to and including 2,000	Up to and including 1,000	No

Table 2. RNG Parameters

In addition to final outcome data, GLI tested raw outcomes consisting of binary output from the main RNG algorithm prior to the application of any scaling algorithms. For a summary of the statistical tests applied to each data set, see *Appendix A*. For a description of the overall test methodology and a description of each test used, see *Appendix B*.

Overall, the RNG passed the battery of tests for each configuration at the 95%, 98%, and 99% confidence levels.

SECTION V - SUMMARY

Overall Evaluation of the Random Number Generator

GLI's conclusion based upon the tests applied to the RNG2.0 RNG data is that this RNG has exhibited random behavior and is suitable for the applications as described herein. If a game utilizes different RNG parameters than the ones listed in this report, the RNG should be resubmitted to test that set of parameters.

APPENDIX A: Statistical Test Summary

					Test Names													
Data Set	**Range**	**Positions**	**Replacement**	**Draws**	**Runs**	**Serial Correlation**	**Interplay Correlation**	**Adjacency Max-Min**	**Adjacency High-Low**	**Adjacency Blocks**	**Coupon Collector**	**Duplicates**	**Overlaps**	**Permutation**	**Total Distribution**	**Total Distribution by Position**	**Count of Counts**	**DieHard**
General Testing 1	Up to and including 100,000	Up to and including 20	Yes	①	X	X	X	X	X		X	X	X		X	X		
General Testing 2	Up to and including 2,000	Up to and including 1,000	No	①	X	X	X	X	X	X	X	X	X	X	X	X	X	
Binary	Not Applicable																	X

Table A 1. Tests Applied

① Different test cases were used for statistical testing while taking into account broad coverage of the RNG parameters listed.

APPENDIX B: Test Descriptions

B.1 **Definitions.** The following terms apply to the below test descriptions. Randomness Device or Random Number Generator (RNG) output may be collected multiple numbers at a time. Each set of numbers is called a draw. Each individual number has a particular order within the *draw*. This is referred to as the number *position*.

B.2 **Distribution Comparisons.** Many of the tests compare an observed numerical distribution with an expected distribution. Unless otherwise specified, this is done by means of a statistical chi-square goodness-of-fit test. The value chi-square is computed in the standard way. If *k* is a possible value, o_k is the observed count of that value, and e_k is the expected count:

$$\chi^2 = \sum_k \frac{(o_k - e_k)^2}{e_k}$$

In the case where expected counts are too small for accurate use of the above formula, values are 'binned' together to ensure an appropriate minimum expected count. The resultant value for chi-square is compared against the distribution for the appropriate number of degrees of freedom. Unusually high (distribution mismatch) or unusually low (insufficient randomness) chi-square values can be causes for data failure.

B.3 **Meta-testing**. Evaluation of groups of *p*-values may include a meta-test for extremity of high or low *p*-values, a meta-test for frequency of high or low *p*-values, and a meta-test for uniformity of *p*-values, as appropriate.

B.4 **Confidence Level**. The statistical tests conducted by GLI are done at a particular *confidence level*. Common confidence levels used include 95%, 98%, and 99%, depending on jurisdictional requirements, and intended use of the RNG. High confidence level testing has low risk of mistakenly failing a good RNG, but higher risk of passing a bad RNG. Lower confidence level testing has increased power of detecting bad RNGs, while also increasing the risk of false failures of good RNGs. Specifically, the confidence level represents the probability that an ideal source of randomness would pass the testing. If an RNG passes statistical tests at a given confidence level, passage at all *higher* confidence levels is implied.

B.5 **Tests**. Some tests are only applicable to certain types of data. Some tests may be applied only to a portion of the data. Some tests may require that the data be parsed, binned, or otherwise transformed, as necessitated by data format.

Adjacency Blocks:

For each draw, the data is first sorted. Then the amount of contiguous blocks of numbers is counted. These statistics are then compared against the expected. For example, if a draw consists of the numbers

1, 5, 4, 2, 6, 9

the data would be sorted and separated into blocks. The resulting statistic would be 3.

Adjacency High-Low:

For each draw, the number of local extrema ('highs' and 'lows') in the data is recorded and compared with the expected distribution. These are also referred to as 'turning points'. For example, if a draw consists of the numbers

1, 3, 5, 7, 2, 9

there would be one local maximum (7) and one local minimum (2). The resulting statistic would be 2.

Adjacency Max-Min:

For each draw, the difference between the maximum and minimum values is calculated and recorded. This is compared with the expected theoretical distribution. For example, if a draw consists of the numbers

2, 3, 6, 7, 4

the resulting statistic would be 5, the difference between the maximum value (7) and the minimum value (2).

Count of Counts:

The Count of Counts test first counts the occurrences of each value in each position of the data. These counts are then tallied and compared with the expected distribution of counts for the draw size and range of values.

Coupon Collector's:

The Coupon Collector's Test is applied positionally. The data is parsed until all possible values have been observed, then the number of values checked is recorded and the count is restarted. This is compared with the expected distribution. For example, if the set of all possible values is {0, 1, 2} and the first position of each draw is

1, 0, 1, 0, 2, 0, 1, 2, …

then all values are observed in the first position by the fifth draw. All values are then observed within the next 3 draws, so the first two statistics for the first position would be 5 and 3.

DieHard:

The DieHard Battery of Tests is a standard assessment of the randomness in raw outcomes generated from an RNG. The collection, designed by George Marsaglia, tests for a variety of patterns in the individual binary bits of RNG output. GLI uses a custom implementation to conduct DieHard testing.

Duplicates:

The Duplicates Test counts the number of times a draw is exactly duplicated in the data. In the case that a particular draw is repeated more than twice, every possible way to generate a duplicate is counted. This is compared against the theoretical distribution to verify that the number of duplicate draws falls within expected bounds. For example, consider the dataset consisting of the following draws of two numbers each.

a) 1, 3
b) 4, 1
c) 1, 3
d) 1, 3
e) 4, 1
f) 3, 1

The duplicate pairs are (*a, c*), (*a, d*), (*c, d*), and (*b, e*), for a total of 4 duplicates. *(f)* is not counted as a duplicate since the draw must match in order as well as values.

Interplay Correlation:

The Interplay Correlation Test measures statistical correlation between different positions of the same draw. For each pair of positions, statistical correlation is calculated as in the Serial Correlation Test. In the case of without replacement data, an adjustment is made to account for the expected resulting negative correlation.

Overlaps:

The Overlaps Test compares consecutive draws for overlapping values. The number of overlapping values is recorded for each pair of draws. This observed distribution of overlaps is then compared against the expected distribution. For example, if the following draws are observed consecutively,

a) 1, 4, 5, 6
b) 4, 1, 7, 6

the number of overlaps would be 3, representing the values 1, 4, and 6.

Permutation:

The Permutation Test is a test applicable to data that represents a reordering of numbers. Each draw can be considered as a permutation of the original ordering. Every permutation can be decomposed into disjoint cycles, which represent the possible positions a number would occupy if the same permutation is applied repeatedly. For each draw, three statistics are collected based on the cycle decomposition:

- The number of cycles.
- The size of the smallest cycle.
- The size of the largest cycle.

Each of these statistics generates a distribution of observations which are compared with their respective expected distributions. For example, if the following draw were observed as a reordering of the numbers from 1 to 6,

1, 3, 5, 4, 2, 6

the cyclic decomposition would be (1)(2 3 5)(4)(6). 1, 4, and 6 remain in their original positions, so they form their own cycles. The values 2, 3, and 5 are shuffled, so they form a single cycle together. The total number of cycles is 4, the smallest cycle has size 1, and the largest cycle has size 3.

Runs:

The Wald-Wolfowitz Runs Test is applied to each position within the draw. A center is established, typically the data median, and the number of 'runs' above and below the center are tallied. Values exactly equal to the center are discarded. This is compared to the expected distribution, which depends on the number of values above and below the center. For example, if the numbers drawn at a particular position were

2, 3, 1, 5, 4, 7, 3, 2, 3, 2, 3, 2, 6, 7, 3, 5

and the established center were the data median of 3, the data would be parsed for runs above 3 and runs below 3.

$$\underline{2, 3, 1}, \overline{5, 4, 7, 3}, \underline{2, 3, 2, 3, 2}, \overline{6, 7, 3, 5}$$

This would be counted as 4 runs.

Serial Correlation:

The Serial Correlation Test measures statistical correlation between consecutive draws of the same position. For each position, the sample Pearson correlation coefficient is calculated. If *X* represents the first number, and *Y* the number that follows, then the coefficient is

$$r = \frac{cov(X, Y)}{s_X s_Y}$$

where *s* denotes the sample standard deviation. The coefficients are used to generate a *p*-value for each position.

Total Distribution:

The Total Distribution Test is a simple tally of all observed values throughout the data. This is compared with the expected distribution. Typically, the expected distribution is a uniform distribution. In the case of unequal weighting of values, an appropriate discrete distribution is used.

Total Distribution by Position:

The Total Distribution by Position Test tallies the observed distribution of values for each position within the draw. Each of these distributions is then compared with the expected.