The Journal of Academic Social Science Studies

International Journal of Social Science

Volume 6 Issue 2, p. 1315-1326, February 2013

STATISTICAL POWER AND PROBABILITIES OF TYPE I ERROR IN TERMS OF SUITABLE NUMBER OF SIMULATIONS IN NONPARAMETRIC TESTS

NONPARAMETRİK TESTLERDE EN UYGUN SİMÜLASYON SAYISINA GÖRE İSTATİSTİKSEL GÜÇ VE I. TİP HATA OLASILIKLARI

Yrd.Doç. Dr. Ötüken SENGER

Kafkas Üniversitesi İktisadi ve İdari Bilimler Fakültesi

Abstract

Recently, simulation techniques have been widely used in social and medical sciences as well as natural and applied sciences. One of the most common fields of application of these simulation techniques is determination of statistical powers and probabilities of type I error of both parametric and nonparametric tests. Simulation number plays a vital role in such deterministic studies. In case of number of simulations not being sufficient for a clear analysis, then study findings may be inconsistent and instable. In contrast, if number of simulations exceeds the suitable number then it means waste of time. In this study, the effects of different numbers of simulations on determination process of statistical powers and probabilities of type I error of nonparametric tests were discussed. Furthermore, optimum numbers of simulations for determining statistical powers and probabilities of type I error were suggested for future researchers. In this context, one of the nonparametric tests which is used for testing data obtained from two samples, namely Wald Wolfowitz runs test was applied and results were generalized for all nonparametric tests. In study, four equal and small sample sizes were used, these were as follows: (5, 5), (10, 10), (15, 15) and (20, 20). Simulation runs were performed for twenty different numbers of simulation. Significance levelα was assumed as 0, 05 for each sample size. Study was performed by taking the prerequisites of normality and homogeneity of variance into account. According to results; if researchers perform 80.000 simulation runs for a sample size of 5, 60.000 for a sample size of 10 and 50.000 for a sample size of 15 and 40.000 for a sample size of 20 they will have the optimum numbers of simulations in practice.

Key Words: Number of simulation, type I error, power of test, normal distribution, homogeneity of variance.

Öz

Son yıllarda, fen bilimlerinin yanı sıra, sosyal ve beşeri bilimler ile sağlık bilimlerinde de simülasyon tekniklerinden oldukça sık faydalanılmaktadır.Simülasyon tekniklerinin en fazla kullanıldığı yerlerden biri de parametrik ve nonparametrik testlerin I. tip hata olasılıkları ve istatistiksel güçlerinin belirlenmesidir.Bu amaçla yapılan çalışmalarda simülasyon sayısı çok önemlidir.Eğer uygulanan simülasyon sayısı yeterli sayıda olmazsa elde edilen sonuçlar tutarlı ve kararlı olmayabilir.Çok fazla sayıda belirlenen simülasyon sayısı ise boşuna zaman kaybına neden olur. Bu çalışmada, farklı simülasyon sayılarının, nonparametrik testlerin, I. tip hata olasılıkları ve istatistiksel güçlerinin tahmininde göstereceği farklılıklar ele alınmış ve araştırmacılara, I. tip hata olasılığı ve testin gücü bakımından kullanmaları gereken optimum düzeyde simülasyon sayıları önerilmiştir. Bu amaçla iki örnekten elde edilen verileri test etmekte kullanılan nonparametrik testlerden Wald Wolfowitz dizi sayıları testinden faydalanılmış ve elde edilen sonuçlar tüm nonparametrik testler için genellenmiştir. Çalışmada dört eşit ve küçük örnek hacmi kullanılmıştır.Kullanılan örnek hacimleri; (5, 5), (10, 10), (15, 15) ve (20, 20) örnek hacimleridir.Simülasyon denemeleri yirmi farklı simülasyon sayısı için gerçekleştirilmiştir. Çalışmada α önem seviyesi, her bir örnek büyüklüğü için 0, 05 olarak kabul edilmiştir. Çalışma normallik ve varyansların homojenliği ön şartları altında yapılmıştır. Çalışmadan elde edilen sonuçlara göre; araştırmacılar, çalışmalarında kullanacakları örnek hacmi 5 ise 80.000, 10 ise 60.000, 15 ise 50.000 ve 20 ise de 40.000 simülasyon gerçekleştirirlerse bu simülasyon sayıları uygulamada yeterlidir.

Anahtar Kelimeler: Simülasyon sayısı, I. tip hata, testin gücü, normal dağılım, varyansların homojenliği.

1. INTRODUCTION

Simulation techniques can be specifically used in order to make a comparison between probabilities of type I error and powers of tests which are equivalent, obtain sampling distributions of newer tests developed by current ones, estimate parameters of these tests and empirically solve insoluble or complicated mathematical problems[$1-6$]. One of the most widely used simulation technique is Monte Carlo simulation technique [$7-12$] . Monte Carlo simulation technique, by using random samples gathered from data of a specific population, experimentally estimates a statistic[11]. Monte Carlo simulation is a leading technique which applies computer simulation programs and random sample techniques in order to make approximate estimations for mathematical or physical problems in terms of values each having the probability of being a solution[13]. By using Monte Carlo simulation model, the original probability model relevant to data and parameters is turned into a probability model which based on data, parameters and action[14]. The core of Monte Carlo simulation is based on law of large numbers[15].

Monte Carlo simulation can be used in both natural and applied sciences and social sciences. In social sciences, statistics are obtained by gathering samples from artificially obtained data, rather than by gathering various samples from the same population. Thus, distribution of obtained sample converges to intensity function of population. Due to advanced computer technologies, such estimations can be made through Monte Carlo simulation[11].

Although they are efficient and productive, validity of statistical theories depends upon to some theoretical assumptions. If assumptions of a theory are supported with research findings then this statistical theory provides valid and efficient implications relating to sample distribution. In contrary, when research findings do not support assumptions of theory one could argue that validity of characteristics of sample distribution tend to be a complex and inextricable issue. As a consequence, one cannot be sure about reliability of theoretical estimations or validity of implications even if the theory has a significant degree of reliability. In such analytical situations, due to being based on not theoretical expectations of sample distribution's characteristics but on empirical estimations, the Monte Carlo simulation well benefits to quantitative researchers[16].

Monte Carlo simulation can be used in order to:

Make statistical estimations based on weak mathematical theory,

Test the null hypothesis in various potential situations,

Evaluate reliability of parametric results in case of contradictory assumptions are made,

Evaluate quality of estimation methods,

Compare characteristics of two or more estimators[11].

In addition to these, Monte Carlo simulation may also be used when assumptions are contravened or when sample distribution cannot be obtained. The statistics theory, when assumptions are contravened, does not provide any indicator about results or how reliable results will be obtained. Such questions can only be answered by using Monte Carlo simulation. Similarly, in case of theoretical sample distribution not being obtained variance of statistic among samples is investigated again by applying Monte Carlo simulation[16].

Monte Carlo simulation, right alongside with its many advantages and eases of use, has also some difficulties in terms of application. When applying Monte Carlo simulation in semi-parametric or nonparametric tests, there arise some problems in simulation of reference data sets that belong to null hypothesis. The most common problem is failure of demotion of model in a specific way with limited numbers of unknown parameters even in null hypothesis[17].

Productivity of Monte Carlo simulation technique, which is widely used in areas such as natural and applied, social and medical sciences and economy, is directly related to number of runs of simulations. Determining suitable number of simulation runs is very vital in terms of both obtaining reliable results and stabilized estimations [18,19]. In practical simulation studies, number of simulation runs generally vary between 1.000-30.000 [20].

The results of this study suggests that there is a significant difference between estimations obtained from 200, 500 or 1.000 simulations and those obtained from 20.000, 50.000 and 100.000 simulations. Such a results may be an indicator of a concern about stability of estimations. Thus, one could argue that number of simulations used in simulation studies play an important role on reliability and stability degree of obtained results.

In this study, effects of variable numbers of simulations on estimation of statistical powers and probabilities of type I error of nonparametric tests were investigated and some suggestions about optimum numbers of simulations for future researchers were made. In this context, one of the nonparametric tests which are used for testing data obtained from two samples, namely Wald Wolfowitz Runs Test was applied and results were generalized for all nonparametric tests.

2. MATERIAL AND METHODS

Material of study consists of random numbers produced by Monte Carlo simulation. Monte Carlo simulation can be applied by using a lot of different analysis programs. SAS system is composed of statistical procedures, mathematical functions and multidimensional programming facilities. Due to these components, SAS system becomes more available among its alternatives in terms of applying Monte Carlo simulation[16]. A SAS program consists of sequential symbols[21]. SAS program is runned by SUBMIT command. RUN procedure is used for performing statistical analyses. RANNOR procedure is applied for obtaining random numbers. In this procedure, Fleishman's power transformation method is used for obtaining random numbers from a normal distribution of which has an average value of 0 and a Standard deviation of 1[16]. In SAS program, SIDES procedure is used for identifying the type of test. If the test is two-sided then SIDES 2 procedure is chosen. In addition, ın one-sided tests SIDES U (right tailed test) and L (left tailed test) procedure is chosen. The assumption of normal distribution is tested by using PROC UMVARIATE procedure in SAS program. PROC NPAR1WAY procedure of SAS program is used for specifying Type I errors and power simulations[22].

In study, SAS 9.00 statistical analysis program is applied and data production and analysis processes were performed by using a Windows 7 compatible Casper computer with dual core, 3GB RAM and 32 byte CPU. SAS syntaxes were programmed by researcher in order to obtain populations from normal distribution and estimate every single test statistic. In programming of syntaxes for WW test, assumptions and data arrangements, applicable hypotheses, test statistics and formulations of decision rules for large and small samples were taken into account. In study, significance level α was 0, 05 for any sample sizes.

Four equal and small sized samples were used. Sample sizes were as follows: (5, 5), (10, 10), (15, 15) and (20, 20). Simulation runs were performed for 20 different numbers of simulations; these were 200, 500, 1.000, 2.000, 5.000, 10.000, 20.000, 30.000, 40.000, 50.000, 60.000, 70.000, 80.000, 90.000, 100.000, 200.000, 300.000, 400.000, 500.000 and 1.000.000. The prerequisites of homogeneity of variance and normality were taken into account during performance. Homogeneity of variance refers to variances of populations from which samples were chosen being similar or equal[23].In Monte Carlo simulation, homogeneity of variance between two samples may be denoted in different ways. According to Penfield; rate of variances of two populations which denoted by $\frac{\sigma_1^2}{\sigma_2^2}$ can be specified as homogeneity of variance[24].Population variance of first sample group is denoted by σ_1^2 while second group's is denoted by σ_2^2. To Zimmerman, rate of standard deviations of two populations is an indicator of homogeneity of variance[25].When they are applied to Monte Carlo simulations; both rates of variances and rates of standard deviations cause the same effects. In study, rate of standard deviations of two populations was specified as an indicator of variance of homogeneity.

3. RESULTS AND SUGGESTIONS

According to simulation results; depending on to the increase in numbers of simulations, one may argue that probabilities of Type I errors and values of statistical power tend to converge. Simulation results show that, in small numbers of simulations (10.000 or smaller), probabilities of Type I errors and values of statistical power differ considerably. This level of difference tends to be higher in small sample sizes. For a sample size of 5 and number of simulation 200, probabilities of Type I error range between %1,3 and %2,7; %1,09 and %2,1 for 500 simulations and %1,4 and %2,6 for 1000 simulations. On the other hand, when number of simulations was increased to 5.000 probabilities of Type I error range between %1,4 and % 1,8; % 1,6 and % 1,8 for 10.000 simulations and %1,5 and % 1,7 for 20.000. As can be seen, the difference between minimum and maximum values of probabilities of Type I error tend to decrease when number of simulations increase. It is shown that the minimum and maximum values of probabilities of Type I error tend to converge for number of simulations 50.000 or more. Similarly, values of statistical power have the same tendency. For a sample size of 5 and number of simulation 200, values of statistical power range between %0,98 and %2; %0,5 and %1 for 500 simulations and %0,8 and %1,4 for 1.000 simulations. On the other hand, when number of simulations was increased to 5.000 values of statistical power range between %1,2 and % 1,6; % 1,4 and % 1,6 for 10.000 simulations and %1,5 and % 1,7 for 20.000 simulations. . It is shown that the minimum and maximum values of statistical power tend to converge or even be equal to each other for number of simulations 60.000 or more.

According to results; when sample size increases the difference between values of probabilities of Type I error and statistical power tend to decrease. For example, for a sample size of 5 and number of simulations 1.000, probabilities of Type I error range between %1,4 and % 2,6 while for a sample size of 20 and number of simulations 1.000 they range between %2,4 and % 3,2.

As shown, increases in number of simulations lead to decreases in difference between values of probabilities of Type I error and statistical power. Thus, more reliable results can be obtained. Both the difference between minimum and maximum values of probabilities of Type I error and statistical power and decreases in values of standard deviations illustrated in tables point to this result. Table 1-4 shows the study results. In table 1, it is shown that for a sample size of 5 and number of simulations 80.000 minimum and maximum values of probabilities of Type I error are almost equal, and standard error is % 0,1. Therefore, one could argue that, for a sample size of 5, suitable number of simulations is 80.000. Again, in table 1, it is shown that for a sample size of 10 and number of simulations 60.000 minimum and maximum values of probabilities of Type I error are almost equal. Put differently, for a sample size of 10, suitable number of simulations is 60.000. In table 2, it is shown that for a sample size of

15 and number of simulations 50.000 minimum and maximum values of probabilities of Type I error are almost equal, and standard error is % 0,1. Therefore, one could argue that, for a sample size of 15, suitable number of simulations is 50.000. Again, in table 2, it is shown that for a sample size of 20 and number of simulations 40.000 minimum and maximum values of probabilities of Type I error are almost equal. Put differently, for a sample size of 20, suitable number of simulations is 40.000.

Table 1.For $\sigma_1:\sigma_2=1$ andn=5 and n=10, suitable number of simulations for probabilities of type I error of WW test

Number of Simulation	$\sigma_1:\sigma_2=1$, n=5				Number of Simulation	$\sigma_1:\sigma_2=1$, n=10			
	Type I Error			Std. Error		Type I Error			Std. Error
	Min	Max	$\bar{X}$	S_x		Min	Max	$\bar{X}$	S_x
200	0,01300	0,02700	0,020	0,020	200	0,03150	0,05850	0,045	0,021
500	0,01088	0,02112	0,016	0,013	500	0,03066	0,05334	0,042	0,013
1.000	0,01400	0,02600	0,020	0,010	1.000	0,02775	0,04625	0,037	0,010
2.000	0,01200	0,01800	0,015	0,007	2.000	0,02870	0,04130	0,035	0,007
5.000	0,01360	0,01840	0,016	0,004	5.000	0,03393	0,04407	0,039	0,004
10.000	0,01598	0,01802	0,017	0,003	10.000	0,03325	0,03675	0,035	0,003
20.000	0,01520	0,01680	0,016	0,002	20.000	0,03360	0,03640	0,035	0,002
30.000	0,01641	0,01760	0,017	0,002	30.000	0,03608	0,03793	0,037	0,002
40.000	0,01568	0,01632	0,016	0,002	40.000	0,03546	0,03654	0,036	0,002
50.000	0,01478	0,01523	0,015	0,001	50.000	0,03652	0,03748	0,037	0,001
60.000	0,01579	0,01621	0,016	0,001	60.000	0,03659	0,03741	0,037	0,001
70.000	0,01582	0,01618	0,016	0,001	70.000	0,03568	0,03632	0,036	0,001
80.000	0,01586	0,01614	0,016	0,001	80.000	0,03773	0,03827	0,038	0,001
90.000	0,01490	0,01511	0,015	0,001	90.000	0,03682	0,03719	0,037	0,001
100.000	0,01692	0,01709	0,017	0,001	100.000	0,03685	0,03715	0,037	0,001
200.000	0,01595	0,01605	0,016	0,001	200.000	0,03693	0,03707	0,037	0,001
300.000	0,01597	0,01603	0,016	0,001	300.000	0,03696	0,03704	0,037	0,001
400.000	0,01598	0,01602	0,016	0,000	400.000	0,03698	0,03702	0,037	0,000
500.000	0,01599	0,01601	0,016	0,000	500.000	0,03699	0,03700	0,037	0,000
1.000.000	0,01599	0,01600	0,016	0,000	1.000.000	0,03700	0,03700	0,037	0,000

Table 2. For $\sigma_1:\sigma_2=1$ and n=15 and n=20, suitable number of simulations for probabilities of type I error of WW test

Number of Simulation	$\sigma_1:\sigma_2=1$, n=15				Number of Simulation	$\sigma_1:\sigma_2=1$, n=20			
	Type I Error			Std. Error		Type I Error			Std. Error
	Min	Max	$\bar{X}$	S_x		Min	Max	$\bar{X}$	S_x
200	0,04125	0,06875	0,055	0,021	200	0,02800	0,04200	0,035	0,020
500	0,03696	0,05904	0,048	0,014	500	0,03444	0,04956	0,042	0,014
1.000	0,03002	0,04598	0,038	0,010	1.000	0,02352	0,03248	0,028	0,010
2.000	0,03192	0,04408	0,038	0,007	2.000	0,03010	0,03990	0,035	0,007
5.000	0,03432	0,04368	0,039	0,004	5.000	0,03115	0,03885	0,035	0,004
10.000	0,03936	0,04264	0,041	0,003	10.000	0,03185	0,03416	0,033	0,003
20.000	0,03860	0,04140	0,040	0,002	20.000	0,03492	0,03708	0,036	0,002
30.000	0,03916	0,04084	0,040	0,002	30.000	0,03532	0,03668	0,036	0,002
40.000	0,04045	0,04155	0,041	0,002	40.000	0,03555	0,03645	0,036	0,002
50.000	0,03952	0,04048	0,040	0,001	50.000	0,03564	0,03636	0,036	0,001
60.000	0,03762	0,03838	0,038	0,001	60.000	0,03669	0,03731	0,037	0,001
70.000	0,03968	0,04032	0,040	0,001	70.000	0,03674	0,03726	0,037	0,001
80.000	0,03974	0,04026	0,040	0,001	80.000	0,03682	0,03719	0,037	0,001
90.000	0,03982	0,04018	0,040	0,001	90.000	0,03586	0,03614	0,036	0,001
100.000	0,03986	0,04014	0,040	0,001	100.000	0,03589	0,03611	0,036	0,001
200.000	0,03894	0,03906	0,039	0,001	200.000	0,03696	0,03704	0,037	0,001
300.000	0,03998	0,04002	0,040	0,001	300.000	0,03598	0,03602	0,036	0,001
400.000	0,03999	0,04000	0,040	0,000	400.000	0,03700	0,03701	0,037	0,000
500.000	0,04000	0,04000	0,040	0,000	500.000	0,03700	0,03700	0,037	0,000
1.000.000	0,04000	0,04000	0,040	0,000	1.000.000	0,03600	0,03600	0,036	0,000

Table 3 and 4 shows results for values of statistical power. In table 3, it is shown that for a sample size of 5 and number of simulations 80.000 minimum and maximum values of statistical power are almost equal, and standard error is % 0,1. Therefore, one could argue that, for a sample size of 5, suitable number of simulations is 80.000. Again, in table 3, it is shown that for a sample size of 10 and number of simulations 70.000 minimum and maximum values of statistical power are almost equal. Put differently, for a sample size of 10, suitable number of simulations is 70.000. In table 4, it is shown that for a sample size of 15 and number of simulations 50.000 minimum and maximum values of statistical power are almost equal, and standard error is % 0,1. Therefore, one could argue that, for a sample size of 15, suitable number of simulations is 50.000. Again, in table 4, it is shown that for a sample size of 20 and number of simulations 40.000 minimum and maximum values of statistical power are almost equal. Put differently, for a sample size of 20, suitable number of simulations is 40.000.

Table3.For σ1:σ2=2 andn=5 and n=10,suitable number of simulations for values of statistical power of WWtest

Number of Simulation	σ1:σ2=2, n=5				Number of Simulation	σ1:σ2=2, n=10			
	Statistical Power			Std. Error		Statistical Power			Std. Error
	Min	Max	$\bar{X}$	S_x		Min	Max	$\bar{X}$	S_x
200	0,00975	0,02025	0,015	0,020	200	0,02450	0,04550	0,035	0,024
500	0,00544	0,01056	0,008	0,013	500	0,03504	0,06096	0,048	0,015
1.000	0,00770	0,01430	0,011	0,009	1.000	0,03825	0,06375	0,051	0,011
2.000	0,01040	0,01560	0,013	0,007	2.000	0,04592	0,06608	0,056	0,007
5.000	0,01190	0,01610	0,014	0,004	5.000	0,05046	0,06554	0,058	0,005
10.000	0,01410	0,01590	0,015	0,003	10.000	0,05035	0,05565	0,053	0,003
20.000	0,01520	0,01680	0,016	0,002	20.000	0,05088	0,05512	0,053	0,002
30.000	0,01448	0,01553	0,015	0,002	30.000	0,05265	0,05535	0,054	0,002
40.000	0,01470	0,01530	0,015	0,001	40.000	0,05319	0,05481	0,054	0,002
50.000	0,01576	0,01624	0,016	0,001	50.000	0,05527	0,05673	0,056	0,001
60.000	0,01481	0,01520	0,015	0,001	60.000	0,05538	0,05662	0,056	0,001
70.000	0,01484	0,01517	0,015	0,001	70.000	0,05351	0,05449	0,054	0,001
80.000	0,01487	0,01514	0,015	0,001	80.000	0,05362	0,05438	0,054	0,001
90.000	0,01490	0,01511	0,015	0,001	90.000	0,05373	0,05427	0,054	0,001
100.000	0,01493	0,01508	0,015	0,001	100.000	0,05378	0,05422	0,054	0,001
200.000	0,01496	0,01505	0,015	0,001	200.000	0,05489	0,05511	0,055	0,001
300.000	0,01497	0,01503	0,015	0,001	300.000	0,05495	0,05506	0,055	0,001
400.000	0,01499	0,01502	0,015	0,000	400.000	0,05594	0,05600	0,056	0,001
500.000	0,01499	0,01501	0,015	0,000	500.000	0,05600	0,05600	0,056	0,000
1.000.000	0,01500	0,01500	0,015	0,000	1.000.000	0,05500	0,05500	0,055	0,000

Table 4. For σ1:σ2=2 and n=15 and n=20, suitable number of simulations for values of statistical power of WW test

Number of Simulation	σ1:σ2=2, n=15				Number of Simulation	σ1:σ2=2, n=20			
	Statistical Power			Std. Error		Statistical Power			Std. Error
	Min	Max	$\bar{X}$	S_x		Min	Max	$\bar{X}$	S_x
200	0,06000	0,10000	0,080	0,023	200	0,09600	0,14400	0,120	0,024
500	0,06468	0,10332	0,084	0,014	500	0,09840	0,14160	0,120	0,015
1.000	0,06162	0,09438	0,078	0,010	1.000	0,08232	0,11368	0,098	0,010
2.000	0,07224	0,09976	0,086	0,007	2.000	0,08944	0,11856	0,104	0,008
5.000	0,07216	0,09184	0,082	0,005	5.000	0,09434	0,11766	0,106	0,005
10.000	0,07872	0,08528	0,082	0,003	10.000	0,09650	0,10350	0,100	0,003
20.000	0,08106	0,08694	0,084	0,002	20.000	0,10088	0,10712	0,104	0,002
30.000	0,07922	0,08278	0,081	0,002	30.000	0,09712	0,10088	0,099	0,002
40.000	0,08085	0,08315	0,082	0,002	40.000	0,09974	0,10226	0,101	0,002
50.000	0,08299	0,08501	0,084	0,001	50.000	0,10098	0,10302	0,102	0,001
60.000	0,08217	0,08383	0,083	0,001	60.000	0,10212	0,10388	0,103	0,001
70.000	0,08333	0,08467	0,084	0,001	70.000	0,10228	0,10372	0,103	0,001
80.000	0,08147	0,08253	0,082	0,001	80.000	0,10348	0,10452	0,104	0,001
90.000	0,08462	0,08538	0,085	0,001	90.000	0,10358	0,10442	0,104	0,001
100.000	0,08371	0,08429	0,084	0,001	100.000	0,10369	0,10431	0,104	0,001
200.000	0,08387	0,08413	0,084	0,001	200.000	0,10190	0,10210	0,102	0,001
300.000	0,08196	0,08204	0,082	0,001	300.000	0,10195	0,10205	0,102	0,001
400.000	0,08300	0,08300	0,083	0,001	400.000	0,10197	0,10203	0,102	0,001
500.000	0,08200	0,08200	0,082	0,000	500.000	0,10200	0,03700	0,102	0,000
1.000.000	0,08300	0,08300	0,083	0,000	1.000.000	0,10300	0,03600	0,103	0,000

4. REFERENCES

1. OLSON, C. L, A MonteCarlo investigation of the robustness of multivariate analysis of variance. Unpublished doctoral dissertation, University of Toronto, Toronto, Canada, 1972.
2. HALPERIN, S, Design of Monte Carlo studies. Paper presented at the meeting of the American Educational Research Association, San Francisco, CA. (ERIC Document Reproduction Service No. ED 121 850), 1976.

3. FISHMAN, G. S., L. R. MOORE, A statistical evaluation of multiplicative congruential random number generators with modulus 2^{31}-1. Journal of the American Statistical Association, 77, 129-136, 1982.
4. MORGAN, B. J. T, Elements of simulation. New York Chapman and Hall, 1984.
5. RIPLEY, B. D, Stochastic simulation. New York: John Wiley & Sons, 1987.
6. PARK, S. K., K. W. Miller, Random number generators: Good ones are hard to find. Communications of the ACM, 31: 1192-1201, 1988.
7. RUBINSTEIN, R. Y, Simulation and the Monte Carlo method.New York John Wiley & Sons, 1981.
8. BRATLEY, P., B. L. FOX and L. E. SCHRAGE, A guide to simulation (2nd ed.). New York: Springer-Verlag, 1987.
9. NASH, J. C, Compact numerical methods for computers: Linear algebra and function minimization (2nd ed.). New York Adam Hilger, 1990.
10. DARLINGTON, R. B, Estimating the true accuracy of regression predictions.Mid-Western Educational Researcher, 9(4), 29-31, 1996.
11. MOONEY, C. Z, Monte Carlo simulation (Sage University Paper series on Quantitative Applications in the Social Sci., series no. 07-116). Thousand Oaks, CA: Sage, 1997.
12. WILCOX, R. R, Comparing variances of two independent groups, British Journal of Mathematical and Statistical Psychology, 55: 169-175, 2002.
13. MERRIAM-WEBSTER, Inc, *Merriam-Webster's Collegiate Dictionary*.10th Edition. Springfield, MA: Merriam-Webster, Inc, 1994.
14. MÜLLER, P, "Simulation Based Optimal Design". Dipak K. DEY and Calyampudi R. RAO (Ed.).*Handbook of Statistics, Vol. 25.* Atlanta: Elsevier B.V, 2005.
15. JIANG, J, *Large Sample Techniques for Statistics*. New York: Springer Science + Business Media, LLC, 2010.
16. FAN, X., FELSOVALYI, A., SIVO, S. A., KEENAN, S. C, *SAS for Monte Carlo Studies: A Guide for Quantitative Researchers.* Cary, North Carolina: SAS Publishing, 2002.
17. ZHU, L, *Nonparametric Monte Carlo Tests and Their Applications.* New York: Springer Science + Business Media, Inc, 2005.
18. KARIAN, Z. A., E. J. Dudewicz, Modern statistical systems, and GPSS simulation: The first course. New York Computer Science Press, 1991.

19. DIAZ-EMPARANZE, I, Is small Monte Carlo analysis a good analysis? Chacking the size power and consistency of a simulation based test. Statistical Papers, 43 (4), 567-577, 2002.
20. MENDEŞ, M, "Uygun Simülasyon Sayısının Belirlenmesi: Monte Carlo Simülasyon Çalışması", Tarım Bilimleri Dergisi, 11(1), 12-15, 2005.
21. DELWICHE, L. D., SLAUGHTER, S. J, *The Little SAS Book*. 4th. Edition. . North Carolina: SAS Institute Inc, 2008.
22. WALKER, G. A., SHOSTAK, J, *Common Statistical Methods for Clinical Research with SAS Examples.* 3rd. Edition. North Carolina: SAS Institute Inc, 2010.
23. VOGT, W. P, *Dictionary of Statistics and Methodology: A Nontechnical Guide for the Social Sciences.*3rd. Edition. Thousand Oaks, California: Sage Publications, 2005.
24. PENFIELD, D. A, "Choosing A Two-Sample Location Test". *Journal of Experimental Education*, 62, 4, 343-350, 1994.
25. ZIMMERMAN, D. W, "Inflation of Type I Error Rates by Unequal Variance Associated with Parametric, Nonparametric, and Rank-Transformation Tests". *Psicologica,* 25, 103-133, 2004.