USE OF POWER ANALYSIS IN CHOOSING APPROPRIATE SAMPLE SIZE FOR QUALITY INSPECTION

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Summary

Selection of an appropriate sample size is one of the most important aspects of any quality inspection. The right sample size enables making valid conclusions about the quality of the product with minimum necessary resources. The choice of sample size and the probability of Type II error (ß) are closely connected. The purpose of this paper is to examine how usage of a statistical power analysis can improve researcher's decision about choosing an appropriate sample size for experimental purposes and quality inspection.

Apart from sample size, the power of a study (1- ß) or the probability that the study will yield significant results is determined by the magnitude of the treatment effect and by the level of statistical significance required (α). The goal of power analysis is to balance values of these three factors to get an appropriate power. Impact of individual changes of each factor on the power was observed through a hypothetical statistical example based on a significance test in which the difference between proportions of two independent samples was estimated. Power and Precision software was used for calculations.

Results of the power analysis have shown that increase in effect size, sample size and/or level of statistical significance lead to an increase in power. This means if power increased and/or effect size and/or level of statistical significance decreased, a larger sample size would be required.

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This paper demonstrates the usefulness of using statistical power analysis in determining appropriate sample size and warns about possible consequences of erroneously selected sample size.

Key words: *statistical power analysis, sample size, effect size, Type I error, quality inspection, independent samples.*

1. INTRODUCTION

A statistical power analysis is typically used before running an experiment as part of quality inspection. Power analysis determines the power or the likelihood that the experiment will yield results that are statistically significant. At the same time, power analysis can determine the likelihood that the observed process has an appropriate quality level.

Power is the probability of rejecting a null hypothesis if the difference between the population mean (or any another population parameter) and a specified value equals a technically significant difference. A technically significant difference is the minimum difference between the population mean (or any another population parameter) and a specified value that the researcher regards as being of practical importance. The specified value can be determined with some quality standards too. If the difference is greater than this, then it is technically important and we would hope to reject the null hypothesis and claim evidence of a difference (Greenfield, Metcalfe, 2007). In this case, it could be concluded that the process does not meet the minimum allowed quality level. In this way, power analysis is a very important element of quality inspection.

Study research is always carried out on a sample of a finite size. It is assumed that results based on the sample represent the entire population. However, due to a random sampling error, results obtained using the sample will rarely be equal to the results obtained on the basis of population. For example, suppose we put in the null hypothesis assuming that the value of the observed population parameter is equal to 0. If the null hypothesis is true, the given parameter obtained on a sample basis can be equal to 0 and if it is not exactly the same as the assumed value, then it is at a reasonable distance to that value. If it appears that the value of the observed parameter calculated on a sample basis deviates significantly from the value 0 then we would have to reject the null hypothesis.

The decision, if the given sample parameter deviates significantly from the same parameter of the population or not, depends primarily on the value of three factors [Sawyer, Ball, 1981, Baroudi, Orlikowski, 1989]. The first factor is the effect size which shows if the phenomenon in the population under a statistical test was considered as either absent (null hypothesis true) or present (null hypothesis false). The absence of the phenomenon implies some specific value for a population parameter [Cohen, 1988, Fern, Monroe, 1996]. The effect size describes the magnitude of the relationship between two variables present in population [Ferguson, Ketchen, 1999].

The second factor is the sample size. Specifically, if the sample size is increasing then it is assumed that the sampling error is reduced, and with the increasing sample size a given parameter should approach the population parameter value. The third factor is the level of safety making the right decision. This level of security and significance is marked by alpha (α) and its value is mainly decided by a researcher on his own.

Those factors are contained in the tests of significance. Significance tests generally have this format:

$$\text{Test Statistic} = \frac{\text{Observed Difference}}{\text{Standard Error}}$$

If you look closely at the previous equation, then it can be concluded that, in fact, the numerator is the observed first factor and the denominator incorporates the second factor because standard error largely depends on the sample size. When the observed effect (observed difference) is large and/or the sample size is large, then the value of the test statistic is also high. After calculating the test statistic, the resulting value is compared to the theoretical value of certain statistical distribution, which depends on the value of the third observed factor (it depends on the value level of significance, which is denoted by alpha) and then the researcher decides on rejecting or not rejecting the null hypothesis. But the significance test contains the potential for two types of error. First type of error or Type I error occurs when you reject the null hypothesis as if it were false, but it is in fact true. Type I error rate is denoted by alpha. For example, if alpha is set at 0.01 and if the null hypothesis is true than 1% of studies will result in a Type I error. On the other hand, the second type of error or Type II error occurs when you do not reject the null hypothesis as if it were true, but it is in fact false [Dumičić, 2005]. Type II error rate is denoted by beta. For example, if beta is set at 0.10 then 10% of all studies will yield nonsignificant results. If we calculate $(1-\beta)$ we will get the power of the test. If the value of beta is high this means that there is a greater likelihood that the study will yield nonsignificant results, and if the value of beta is high the power of the test is lower. If the power is low, there is little chance of detecting an important difference which means that we want the greatest power possible, otherwise the study will be a waste of money and time.

Power is determined by three factors – effect size, sample size and level of statistical significance (alpha) because the power shows the likelihood that the study will yield statistical significance and the statistical significance of a study depends on these three factors. Power, effect size, sample size and alpha make the system in the sense that if any of the three elements are given, the fourth element is also defined. Because the researcher has limited resources, the main goal of a power analysis is to find an appropriate balance between these four factors considering the goals of the experiment or quality inspection, and the available resources. This paper will examine how change in each factor used in a power analysis affects the value of power. Indirectly, the impact of change of a certain factor on the sample size will be examined too.

Van Belle (2008) noted that the first question, and frequently the last, facing researchers is the needed sample size. He also highlights the problem of research-

ers being usually less interested in questions like Type I error or Type II error. For Montgomery and Runger (2011), power is a very descriptive and concise measure of the sensitivity of a statistical test. Sensitivity is understood as the ability of the test to detect differences. Black (2011) translates Type II errors to lost opportunities, poor product quality and failure to react to the marketplace because failure to reject the null hypothesis may mean staying with the status quo, not implementing a new process or not making adjustments. According to that, Type II error and power are playing an important role in business statistical decision making. Hoenig and Heisy (2001) have gone one step further and they warn about inappropriate uses of power analysis. Cohen's works are shown as the most important references (Cohen, 1988). All authors agree that sample size planning is often important but almost always difficult. It is surprising that for such an important issue a small amount of literature is published (Lenth, 2001). In spite of this, it is remarkable that there is a growing amount of software for sample size determination (Thomas, Krebs, 1997, Lewis, 2000, Lenth, 2001).

In this paper, a power analysis will be done on a simple example which discusses an estimate of differences in proportions based on two independent samples. The simple example is used because the goal is to emphasize the principle and procedure of a power analysis, and not the problem used in the example.

The main limitation of the paper is the fact that it uses an imaginary problem. But the problem is purposely defined in a way which enables, with minor corrections, easy practical use. This means that the paper can serve as a practice document for organizations interested in choosing an appropriate sample size for experimental purposes.

This paper aims to emphasize the importance and need for using power analysis in the planning process of conducting research and quality inspection. By using power analysis, the likelihood of a false conclusion can be reduced and, most importantly, can improve a researcher's decision about choosing an appropriate sample size for experimental and quality inspection purposes.

2. DATA AND METHODS

The main and most common problem in research and in quality inspection is how with limited resources, and above all with limited funds, to conduct an appropriate study that will ultimately bring significant results. The quality inspection must give certain valid conclusions about the quality of process. For this reason, each researcher must know what happens with the results of the analysis and must be familiar with the risks involved if the value of relevant factors is changed (effect size, sample size or alpha). Impact of changes in the value of each factor on the power value will be considered on a simple example in which hypothetical data are used.

Company K&B has created a new remedy for baldness. It is known that 30% of people who do not use any anti-baldness treatment showed some level of baldness.

Existing anti-baldness drug from company K&B which is on the market, reduces the likelihood of baldness by 10%. The company will go into mass production and sale of a new drug for baldness if it becomes evident that the new drug is better than the present or if the new drug appears more likely to reduce the appearance of baldness. It is assumed that the drug reduces the likelihood of baldness by 15% and the initial value is so set at 0.15. In this way the company has stated demands after certain products of better quality. In fact, this is a case of quality inspection.

For testing the assumptions two random samples of persons of equal size will be used. The first sample of persons will serve as a control group that will not be treated with medication (control group) while the second sample of people will be treated with new anti-baldness medication (treatment group). The company has sufficient funds to conduct testing of over 200 people and so the initial sample sizes are equal to 100.

In this situation a two-sided test doesn't make much sense because we want to test for a drug that reduces the probability of baldness, and not for one that increases the probability. Therefore, in this case, we use a one-tail test. The initial value of significance level is 5% what means that the alpha is equal to 0.05.

To be able to calculate the probability of Type II error or statistical power, apart from the sample size and significance level, the effect size has to be defined as well. The expected proportion of bald people in the first population (the population of persons who do not use anti-baldness medication) is 0.30 and this can be expressed as p_1=0.30. On the other hand, if the new drug will be used, it is expected that the proportion of bald people is reduced by 0.15. This means that in the second population (population of people who are using the medicine for baldness) there is supposed to be 15% of bald people and this can be expressed as p_2=0.15. Therefore, the effect size is equal to 0.15 (p_1-p_2=0.30-0.15=0.15).

Once the effect size, the alpha and the sample size have been defined, the probability of error Type II will be determined with the help of software, and more importantly, the power will be determined. The calculation is performed in the program Power and Precision v4 [Borenstein, et. al., 2001].

Figure 1: The power for given example

Group	Proportion Positive	N Per Group	Standard Error	95% Lower	95% Upper
Control	0,30	100			
Treated	0,15	100			
Rate Difference	0,15	200	0,06	0,05	0,25
Alpha= 0,050, Tails= 1			Power	82%	

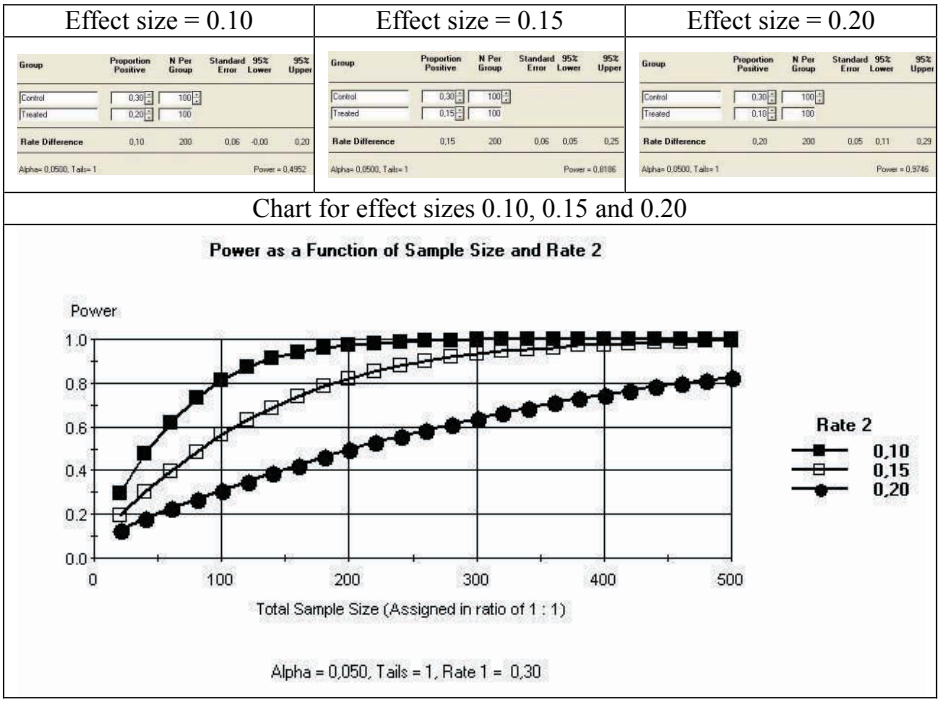
Results show that the power of the test or the probability of not committing error Type II, assuming that both samples are the same size of 100 subjects, is equal to 82%. It should be noted that the program, apart from the ability to directly calculate the power, has the ability of tabular and graphical presentation of power which enables more intuitive reasoning about the movement of the power. The next sections of the paper will discuss what happens with the power if one of the three factors which determine the value of the power change and if the other two factors remain unchanged at the same time.

3. RESULTS AND DISCUSSION

3.1. Impact of effect size on the power

In the observed example it is assumed that the drug reduces the number of bald people by 15%, but it is not necessarily so. It may be that the drug reduces the proportion of bald people more or less than 0.15. To examine the effect size on the power, two more effect sizes will be added to the existing effect size. The present effect size is equal to 0.15. If it is assumed that the drug reduces the proportion of bald people by less than 0.15, for example, just by 0.10 (in this case is p_2=0.20) then the effect

Figure 2: Power for different effect sizes



size is equal to 0.10 (p_1-p_2=0.30-0.20=0.10) and it is less than before. If it is assumed that the drug reduces the proportion of bald men by more than 0.15, for example, by 0.20 (in this case p_2=0.10) then the effect size is equal to 0.20 (p_1-p_2=0.30-0.10=0.20) and it is greater than before. So, now we are looking at the three levels of the effect size (0.10, 0.15 and 0.20). If the remaining two factors are kept fixed, i.e. if a one-way test with alpha equal to 0.05 is still implemented and if the size of both samples is equal to 100, power could be calculated for each effect size. This will be done using Power and Precision and the results are shown in Figure 2.

If alpha was equal to 0.05, sample sizes were equal to 100 and if the effect size was equal to 0.10 then the power would be equal to 0.4952 and in this case it can be said that the likelihood that the study will yield a statistically significant effect would be 49.52%. If alpha and sample size were kept on a given level, but we increased the effect size to 0.15, than the power would be equal to 0.8186. And in the third case, if the true effect was 20 percentage points, based on given levels of alpha and sample size, the power would be 0.9746.

If you consider the movement of effect size and power, it can be noted that they have the same direction of movement. This means that if the effect size is increased, the power increases as well. In practice it is sometimes difficult to find an appropriate effect size and hence Cohen [Cohen, 1988, 1992] has suggested conventional values for "small", "medium" and "large" effects in social sciences. However, Cohen warns that these conventions should not be used routinely, since it is preferable to select an effect size based on the substantive issues involved in the specific study.

The graph in Figure 2 reveals that if the greater effect size is observed, a smaller sample size is needed to obtain the same level of power. This means that if it the researcher wants to observe very small changes in the process, more sample units will have to be used to obtain a certain level of power or a certain level of likelihood that the study will yield significant results.

3.2. Impact of alpha on the power

The second factor on which the value of power depends is the level of statistical significance or alpha. The initial value of the level of statistical significance was set at a value of 0.05. For the value of alpha the values of 0.01 and 0.10 are often taken. With the initial value of effect size and sample size in the example, the power for all three levels of statistical significance will be calculated.

If the alpha was equal to 0.01 for the given effect size and sample size, the value of power would be 0.5860. If we set the alpha to the value of 0.05, the power would be 0.8186 and if alpha was 0.10 then the power would be 0.8996. It can be concluded that if we increase alpha we increase the likelihood of a Type I error if the null is true, but at the same time we decrease the likelihood of a Type II error if the null is false. In other words, as we can see from Figure 3, if we increase alpha, the power increases as well.

Figure 3: Power for different alphas

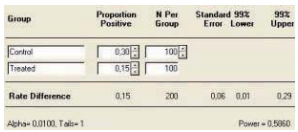
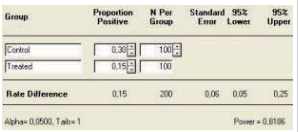
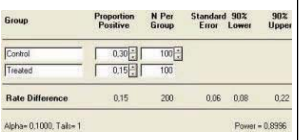
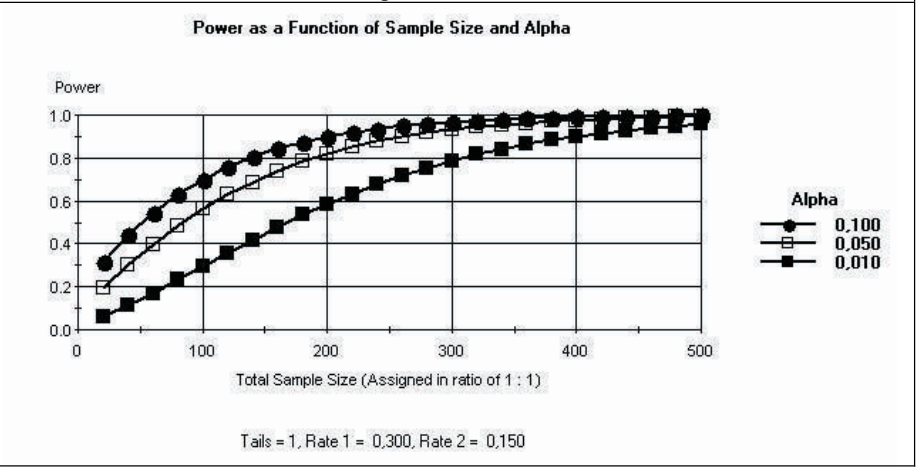
Alpha = 0.01	Alpha = 0.05	Alpha = 0.10
		

Chart for alphas 0.01, 0.05 and 0.10



It is remarkable that if the alpha value was higher, a smaller sample size in the study would be needed to obtain the same level of power. In other words, less sample units would be needed to reach an appropriate power if the value of statistical significance was higher.

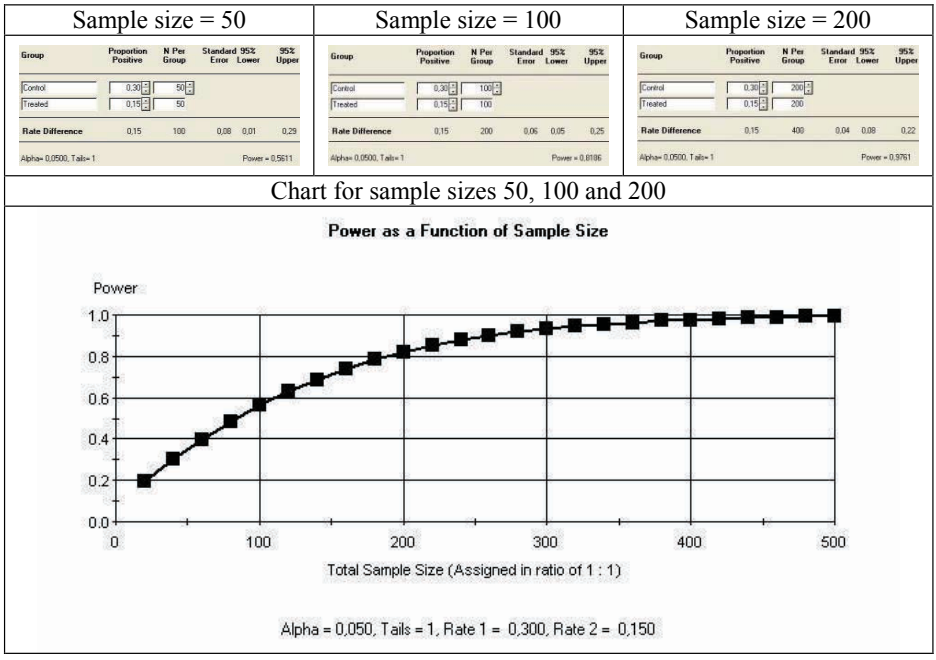
3.3. Impact of sample size on the power

In practice, the sample size which a researcher would choose often depends on the limited resources that the researcher has at his disposal, and the sample size is mostly or entirely based on non-statistical criteria [Lenth, 2001]. It is necessary to take into account that sometimes the number of units available for selection in the sample is substantially limited, for example, if you examine a very rare disease. Also, if a drug is tested against some diseases for which the exact effects (positive and negative) have not yet been determined, it is necessary to observe the ethical side of the problem and in this case it is necessary to have a sample size which contains the minimum required number of persons which ensure obtaining significant results. Everything else above this value represents an unnecessary risk of exposure for persons in the sample.

Since control and treatment group are observed, they represent two populations and because of that, two samples are needed for the purpose of testing. In the example, 100 people were taken as a starting sample size, which means that 200 people should be included in the research. For studies that involve two groups, power is generally maximized when the subjects are divided evenly between two groups, but it is not absolutely necessary to have samples of the same size. In order to determine the movement of the power depending on the change in the sample size, except for sample size 100, power will be determined for sample sizes 50 and 200. Of course, the values of effect size and alpha will remain at their initial levels.

For the sample size 50 the power would be 0.5611. If we doubled the sample size to 100 the power would be 0.8186. If we further raised the sample size to 200 the power would be 0.9761. The conclusion is obvious, for a given effect size and alpha, increasing the sample size will increase the power. This means that if the researcher wants to have an increased power, he has to form a bigger sample. It can be concluded that the power and sample size are in positive correlation.

Figure 4: Power for different sample sizes



4. CONFIDENCE INTERVALS

Researchers want to know whether or not the treatment has any impact and what the size of this impact might be. The first issue can be answered through signifi-

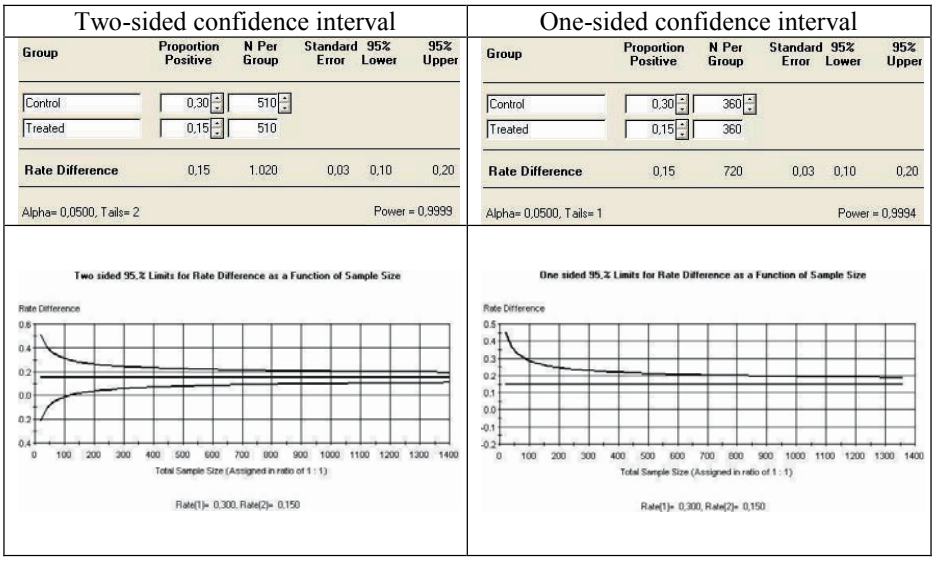
cance tests and the second issue through confidence intervals. For solving the first issue, power analysis is used and for solving the second issue precision analysis is used. Determination of the size of the impact is very important in planning investments for improving quality.

Power shows the likelihood that a study will yield a significant effect and depends on factors that control statistical significance (effect size, alpha, sample size). On the other hand, precision shows the width of the confidence interval surrounding the effect size estimate and depends on factors which control the confidence interval width (confidence level, sample size).

When a significance test is used, it only indicates whether there is or is not any exactly defined impact, but with the use of confidence intervals the focus is on the magnitude of the effect, while confidence intervals point out the amount of confidence that the population effect lies within a given range.

For calculating the confidence interval, data from the beginning of our example will be used. The response rate for the control is expected to be about 30% (p_1=0.30) and for the treated group it is expected to be about 15% (p_2=0.15). The aim is to be able to report the difference in response rates with a 95% confidence interval of plus/minus 5 percentage points. In each group there are the same number of persons (n_1=n_2). Alpha is set at 0.05. To calculate the needed sample size and the power Power and Precision v4 will be used.

Figure 5: Confidence intervals



To obtain a given level of precision, a sample size of 510 units is needed for the control group and for the treated group (this means that 1020 units are needed overall). With this sample size and with the alpha set at 0.05, the power would be 0.9999 to get a statistically significant effect. This is valid for a two-sided confidence interval, but if we look at a one-sided confidence interval at a given level of precision, a sample size of 360 units would be needed and then the power would be 0.9994.

It can be concluded from Figure 5 that increasing the sample size leads to a narrower confidence interval. In fact, the confidence interval will constantly decrease with the increase in sample size, until the sample size is equal to population.

5. CONCLUSION

Statistical power analysis helps researchers to choose an appropriate sample size which is needed to enable statistical judgments that are accurate and reliable. Power analysis indicates the likelihood that the study will yield a significant effect and this is the reason why it must be used for the purposes of planning an experiment. Power analysis is very useful in quality inspection. In this case, power analysis gives an indication of the likelihood that the observed process has a certain quality or not.

Value of the power depends on three factors – sample effect, alpha and sample size. A researcher must find appropriate levels of those factors to achieve a satisfactory level of power. In most cases, the researcher will target the power at the value of 80% but this does not have a scientific base and it depends on different cases, objects and purposes of the research.

The main problems facing the researcher are limited resources. It is known that the larger the sample size, the less the sampling error should be because the sample is more like the population. Certainly it would be best to carry out the research in the entire population, but in most cases this is not possible due to limited financial resources, limited time for research or because of a limited range of spatial research. Of the three factors that influence the value of the power, sample size is therefore the most limiting factor in conducting a power analysis. For this reason, most researchers will first determine the maximum size of the sample, which they can have with their limitations, and then they will try to vary the remaining two factors in order to obtain a satisfactory level of the power.

Therefore it is very important to know how changing certain factors influence the final value of the power. This paper has showed that an increase in each of the three factors individually affect the increase in power, but it should be noted that an increase in the value of the corresponding factor does not proportionally increase the power and the change in each factor has a different intensity of impact on the power. Also, the target value of 0.80 for the power is fairly common and also somewhat minimal. Some authors argue for a higher power but as the power increases, the required sample size increases at an increasing rate (Lenth, 2001).

In order to avoid unnecessary waste of time and money, it is highly recommended to use statistical power analysis. In this way, the likelihood that a study will yield a nonsignificant effect could be minimized. At the same time, valid conclusions about the quality of the process could be made at first inspection. Because of that, additional quality inspections of the same process and costs connected to them could be avoided.

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UPOTREBA ANALIZE SNAGE TESTA U PRONALAŽENJU ODGOVARAJUĆE VELIČINE UZORKA ZA POTREBE KONTROLE KVALITETE

Ksenija Dumičić [3] **&** ***Berislav Žmuk*** [4]

Sažetak

Izbor odgovarajuće veličine uzorka jedan je od najvažnijih problema prilikom provođenja kontrole kvalitete. Odgovarajuća veličina uzorka omogućava donošenje valjanih zaključaka o kvaliteti proizvoda korištenjem minimalne razine potrebnih resursa. Izbor veličine uzorka i vjerojatnost pogreške tipa II (ß) usko su povezani. Cilj ovog rada je istražiti kako analiza snage testa može pomoći istraživaču u odabiru odgovarajuće veličine uzorka za potrebe provođenja određenog eksperimenta i kontrole kvalitete.

Osim veličine uzorka, snaga testa (1- ß) odnosno vjerojatnost da će istraživanje pokazati signifikantne rezultate određena je veličinom efekta tretmana i razinom tražene razine signifikantnosti (alfa). Cilj analize snage testa je da pronađe ravnotežu između tih tri faktora kako bi se postigla zadovoljavajuća razina snaga testa. Utjecaj pojedinačnih promjena svakog od faktora na vrijednost snage testa promatrano je primjenom hipotetičkog statističkog testa u kojem se testirala vrijednost razlike proporcija na dva nezavisna uzorka. Za potrebe izračuna korišten je program Power and Precision.

Rezultati analize snage testa pokazali su da povećanje veličine efekta, veličine uzorka i/ili povećanje razine značajnosti utječe na povećanje snage testa. Iz navedenog proizlazi da se povećanjem snage testa, veličinom efekta i/ili povećanjem razine značajnosti smanjuje potrebna veličina uzorka.

Ovim radom ukazuje se na korisnost primjene statističke analize snage testa u određivanju optimalne veličine uzorka te se upućuje na posljedice pogrešno izabrane veličine uzorka.

Ključne riječi: *analiza snage testa, veličina uzorka, veličina efekta, pogreška tipa I, kontrola kvalitete, nezavisne proporcije.*

JEL klasifikacija: L15

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