SCIENTIFIC PUBLICATIONS OF THE STATE UNIVERSITY OF NOVI PAZAR
SERIES A: APPL. MATH. INFORM. AND MECH. Vol. 17, 2, 2025, 99–108

On the Distribution of Quantile-Zone Test Statistic

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Abstract: Present paper offers more precise specific theoretical description of the distribution of the quantile-zone test statistic. It is manifested by redefining some of its aspects, elaborating on some of its propositions concerning the distribution of underlying quantile-zone function, calculating its numerical characteristics and proving the independence on parameters of testing sample variable. Empirical descriptions by distribution tables and graphical ilustrations are also given. The paper gives an important connection on idea and application development, as well as the applicability verification and new comparative analyses in normality testing.

Keywords and phrases: quantile-zone test, quantile-zone function, normality testing, 3-sigma rule, parameters.

2020 MSC. Primary: 62E17; Secondary: 62E10, 62E17, 62G30, 62Q05.

1 Introduction

General idea of this research comes from several papers dealing with the normality of distribution testing and analysis in general [4, 3]. Part of the research deals even with the quality control [7, 8]. Since normality testing [1], multivariate normality testing [2] and its applications [5] have been very important lately, it might be useful to know more on the quantile-zone distribution which was intended for normality testing.

Though the quantile-zone test statistic (and its distribution) applied in normality testing has yielded some noteworhty results [4], it and its motivating ideas [7] lack certain specifications, additions and redefining so that its application can be improved. This is also important since more applicable test with similar idea has also yielded good results [3].

This paper aims to addres the gap that has occured by researche requirement for more specific theoretical description of quantile-zone distribution and its empirical description via Monte-Carlo simulations.

Following sections elaborate on preliminaries needed and results of the paper. There are also concluding remarks.

Manuscript received November 11, 2025; accepted February 20, 2026

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https://doi.org/10.46793/SPSUNP2502.099A

2 Preliminaries

Normal distribution variates are distributed by the 3σ rule, hence the sample elements will be approximately distributed by it. The 3σ rule is interpretable as per Figure 1.

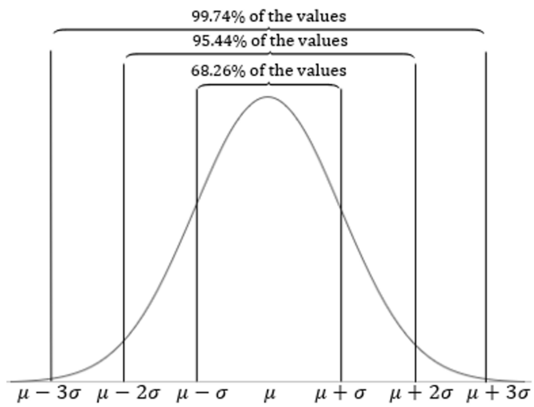

Figure 1. The 3σ rule.

Instead of values 1, 2 and 3 (as multiplicators of σ), in figure 1, values 1, 1.96 and 2.58 can be used with percent of 68.26, 95 and 99, respectively. This variant of 3σ rule is also called "the adjusted 3σ rule" [3]. Since $F_n^*(x) \to F(x)$ $(n \to +\infty)$, $x \in \mathbb{R}$ [9] some analogy might be used.

Assumption 2.1. *Let F_n^* be the empirical distribution function (EDF) of a given random sample $X_1, X_2, \ldots, X_n$, $n \in \mathbb{N}$ distributed as $X \sim \mathcal{N}(\mu, \sigma^2), \mu, \sigma \in \mathbb{R}, \sigma > 0$ with the cumulative distribution function (CDF) F and $F_{\mu \pm i\sigma}$, $i = 1,2,3$ being the CDFs of variables with distributions $\mathcal{N}(\mu \pm i\sigma, \sigma^2)$ respectively.*

The expression

$$F_{\mu+2.58\sigma}(x) < F_{\mu+1.96\sigma}(x) < F_{\mu+\sigma}(x) < F(x) < F_{\mu-\sigma}(x) < F_{\mu-1.96\sigma}(x) < F_{\mu-2.58\sigma}(x) \quad (1)$$

holds for any $x \in \mathbb{R}$. For n large enough, (1) will also hold when F is replaced with F_n^*. Using this fact, F_n^* can be used for goodness of fit by the following function.

Definition 2.1. *Quantile-zone function is function $q_{zone} : \mathbb{R} \to \{1, 1.96, 2.58, 2.81\}$ defined with*

$$q_{zone}(x) = \begin{cases} 1, & F_{\mu+\sigma}(x) < F_n^*(x) < F(x) \vee F(x) < F_n^*(x) < F_{\mu-\sigma}(x) \\ 1.96, & F_{\mu+1.96\sigma}(x) < F_n^*(x) < F_{\mu+\sigma}(x) \vee F_{\mu-\sigma}(x) < F_n^*(x) < F_{\mu-1.96\sigma}(x) \\ 2.58, & F_{\mu+2.58\sigma}(x) < F_n^*(x) < F_{\mu+1.96\sigma}(x) \vee F_{\mu-1.96\sigma}(x) < F_n^*(x) < F_{\mu-2.58\sigma}(x) \\ 2.81, & F_n^*(x) < F_{\mu+2.58\sigma}(x) \vee F_n^*(x) > F_{\mu-2.58\sigma}(x) \end{cases}$$

for all $x \in \mathbb{R}$.

This definition is graphically ilustrated in Figure 2. Thought any other value larger than

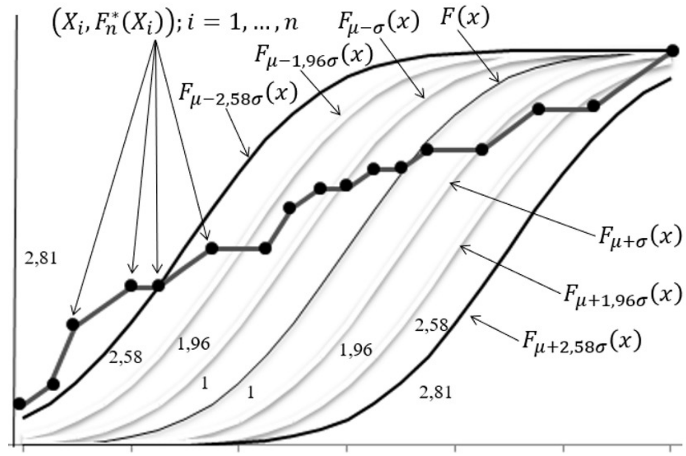

Figure 2. The quantile-zone function ilustrated.

2.58 can be chosen instead of 2.81, this number is chosen due to

$$F^{-1}\left(\frac{F(2.58)+\lim_{x\to+\infty}F(x)}{2}\right) = 2.81,$$

$$\text{as well as}\quad F^{-1}\left(\frac{\lim_{x\to-\infty}F(x)+F(-2.58)}{2}\right) = -2.81.$$

Definition 2.2. *Quantile-zone distribution is the distribution of statistic*

$$\bar{V}_n = \frac{1}{n}\sum_{i=1}^{n} q_{zone}(X_i)$$

under the Assumption 2.1.

In [4] as quantile-zone test of normality test statistic $\bar{V}_n$ is used. Note that in the article where this distribution has been introduced, full analogy with the 3σ rule has been used. Since the 3σ rule does not apply for EDF in relation to CDF, the description of the distribution in that article is only for illustration purpose. The following section deals with some more precise properties of the distributions of both $q_{\text{zone}}(X)$ and $\bar{V}_n$ than given in [4]. Therefore, this article gives description of the distribution that can be considered precise in terms of theoretical conclusions that can be extracted.

The distribution tables in [4] are generated in a way that for some probabilities quantiles have been calculated using bisection method though given quantiles cannot occur empirically. Here the tables are generated so that quantiles are obtainable empirically.

3 Results

Let $Y_1, Y_2, \dots, Y_n$ be ascendingly sorted sample $X_1, X_2, \dots, X_n$, and

$$n_{\max} = \sum_{i=1}^{n} I\left(X_i = \max_{j=1,\dots,n} X_j\right).$$

Proposition 3.1. *Let the Assumption 2.1 hold. The distribution of statistic* $q_{zone}(Y_i)$, $i = 1, \dots, n_{\max} - 1$ *is given with*

$$q_{zone}(Y_i) : \begin{pmatrix} 1 & 1.96 & 2.58 & 2.81 \\ p_1(n) & p_{1.96}(n) & p_{2.58}(n) & p_{2.81}(n) \end{pmatrix},$$

where $p_1(n) < p_{1.96}(n) < p_{2.58}(n) < p_{2.81}(n)$, $\lim_{n\to+\infty} p_1(n) = 1$ *and* $\lim_{n\to+\infty} p_j(n) = 0$, $j = 1.96, 2.58, 2.81$. *The distribution of statistic* $q_{zone}(Y_i)$, $i = 1, \dots, n_{\max} - 1$ *is given with* $P(q_{zone}(Y_i) = 2.81) = 1$.

Proof. For $i \in \{1, \dots, n_{\max}\}$, the proposition holds based on the Glivenko-Cantelly theorem [9]. Namely, since $F_{\mu+\sigma}(x) < F(x) < F_{\mu-\sigma}(x)$ and $F_n^*(x) \xrightarrow{P} F(x)$ $(n \to +\infty)$ hold for all $x \in \mathbb{R}$, after certain $n \in \mathbb{N}$ is reached, $F_{\mu+\sigma}(x) < F_n^*(x) < F_{\mu-\sigma}(x)$ will hold as well. Hence, $q_{\text{zone}}(Y_i) = 1$ will also hold. However, for small $n \in \mathbb{N}$, $q_{\text{zone}}(Y_i) \in \{1.96, 2.58, 2.81\}$ is possible as well.

If $i \in \{n_{\max} + 1, \dots, n\}$, then, since $Y_i = Y_n = \max_{j=1,\dots,n} X_j$,

$$F_n^*(Y_i) = \frac{1}{n} \sum_{j=1}^{n} I(Y_j \le Y_i) = \frac{n}{n} = 1$$

holds. Hence,

$$F_n^*(Y_i) > F_{\mu-3\sigma}(Y_i) \quad \Leftrightarrow \quad q_{\text{zone}}(Y_i) = 2.81 \quad \Rightarrow \quad P(q_{\text{zone}}(Y_i) = 2.81) = 1.$$

□

Remark 3.1. *Simulations yield that for n as small as* $n = 5$, *excluding the maximum value,* $q_{zone}(Y_i) \in \{1.96, 2.58, 2.81\}$ *occurs in less than 3% of cases.*

Proposition 3.2. *Let the Assumption 2.1 hold. Let* $E(q_{zone}(X)) = E_1$ *and* $E\left((q_{zone}(X))^2\right) = E_2$. *Then*

$$E(\bar{V}_n) = \frac{1}{n}\left((n - n_{\max})E_1 + 2.81 \cdot n_{\max}\right) \quad \text{and} \quad D(\bar{V}_n) = \frac{n-1}{n^2}\left(E_2 + E_1^2 + 5.62 \cdot E_1\right) \quad (2)$$

Proof. Using the definition of $\bar{V}_n$

$$\begin{aligned} E(\bar{V}_n) &= E\left(\frac{1}{n}\sum_{i=1}^{n} q_{\text{zone}}(X_i)\right) = E\left(\frac{1}{n}\sum_{i=1}^{n} q_{\text{zone}}(Y_i)\right) \\ &= \frac{1}{n}\left(\sum_{i=1}^{n-n_{\max}} E(q_{\text{zone}}(Y_i)) + \sum_{i=n-n_{\max}+1}^{n} E(q_{\text{zone}}(Y_i))\right) \qquad (3) \\ &= \frac{1}{n}\left((n - n_{\max})E_1 + 2.81 \cdot n_{\max}\right), \end{aligned}$$

and

$$
\begin{aligned}
E(\bar{V}_n^2) &= E\left(\left(\frac{1}{n}\sum_{i=1}^{n} q_{\text{zone}}(X_i)\right)^2\right) \\
&= E\left(\frac{1}{n^2}\left(\sum_{i=1}^{n}(q_{\text{zone}}(X_i))^2 + 2\sum_{i\neq j} q_{\text{zone}}(X_i)\cdot q_{\text{zone}}(X_j)\right)\right) \\
&= \frac{1}{n^2}\left(\sum_{i=1}^{n-n_{\max}} E(q_{\text{zone}}(Y_i))^2 + \sum_{i=n-n_{\max}+1}^{n} E(q_{\text{zone}}(Y_i))^2\right. \\
&\quad + 2\left(\sum_{i=1}^{n-n_{\max}} \sum_{\substack{j=1 \\ j\neq i}}^{n-n_{\max}} E(q_{\text{zone}}(Y_i)\cdot q_{\text{zone}}(Y_i))\right. \\
&\quad + 2\sum_{i=1}^{n-n_{\max}} \sum_{j=n-n_{\max}+1}^{n} E(q_{\text{zone}}(Y_i)\cdot q_{\text{zone}}(Y_i)) \qquad (4) \\
&\quad \left.\left. + \sum_{i=n-n_{\max}+1}^{n} \sum_{\substack{j=n-n_{\max}+1 \\ i\neq}}^{n} E(q_{\text{zone}}(Y_i)\cdot q_{\text{zone}}(Y_i))\right)\right) \\
&= \frac{1}{n^2}\left((n-n_{\max})E_2 + n_{\max}\cdot 2.81^2\right. \\
&\quad \left. + 2\left(\binom{n-n_{\max}}{2}E_1^2 + 2n_{\max}(n-n_{\max})\cdot 2.81E_1 + \binom{n_{\max}}{2}2.81^2\right)\right) \\
&= \ ((n-n_{\max})E_2 + (n-n_{\max})(n-n_{\max}-1)E_1^2 \\
&\quad + 11.24n_{\max}(n-n_{\max})E_1 + 7.90n_{\max}^2)
\end{aligned}
$$

are obtained. Putting the results in variance formula,

$$D(\bar{V}_n) = E(\bar{V}_n^2) - (E(\bar{V}_n))^2 = \frac{(n-n_{\max})(E_2 + E_1^2 + 5.62n_{\max}E_1)}{n^2}$$

is obtained, which completes the proof. □

Since the normal distribution is continuous, in a sample of a normally distributed variable, each modality generally appears no more than once, but in certain intervals there are more modalities than in others. Therefore, it can be assumed that the maximum appears no more than once, i.e. $n_{\max} = 1$. In that case, the following holds:

$$E(V) = \frac{(n-1)E_1 + 2.81}{n} \qquad \text{and} \qquad D(V) = \frac{(n-1)(E_2 + E_1^2 + 5.62\cdot E_1)}{n^2}.$$

Proposition 3.3. *Let the Assumption 2.1 hold. The distribution of statistic $\bar{V}_n$ does not depend on parameters of variable X distribution when those parameters are known.*

Proof. Based on Proposition 3.1, the distribution of variable $q_{\text{zone}}(X_i)$, $i = 1,\ldots,n$, and therefore the distribution of statistic $\bar{V}_n$, does not depend on choice of parameters of variable X, except possibly in terms of sample size n for which the distributions will coincide for different parameters. However, since convergence $p_1(n) \to 1\,(n \to +\infty)$ is a consequence of the convergence of the statistic D_n to the Kolmogorov's distribution, which does not depend on the choice of the parameters of variable X, this convergence, and consequently $p_j(n) \to 0\,(n \to +\infty)$, $j = 1.96, 2.58, 2.81$ (since their sum equals 1), are not determined by the choice of the parameters of variable X. □

The EDF, i.e., its value for sample elements as arguments, depends on sample size and frequency of each sample element less than or equal to the referent one. This means that the sample $F_n^*(X_1), F_n^*(X_2), \ldots, F_n^*(X_n)$, $n \in \mathbb{N}$ has mutually dependent random variables as elements. Hence, the same goes for the sample $q_{\text{zone}}(X_1), q_{\text{zone}}(X_2), \ldots, q_{\text{zone}}(X_n); n \in \mathbb{N}$. In that case, the central limit theorem does not apply to statistic $\bar{V}_n$ [3], and its distribution is determinable only via simulations.

In the following table, we offer the distribution table of statistic $\bar{V}_n$, i.e., values q obtained from

$$P(\bar{V}_n \leq q \mid X : N(\mu, \sigma^2)) = p.$$

Here, n is the sample size. It is impossible to simulate critical values for every sample size. For sample sizes, or values p and q, that are not available in the table, a convenient approximation should be used, for example, the bisection method. We used 100,000 Monte Carlo simulations for each sample size in Table 1.

Table 1. $F_{\bar{V}_n}(q) = P(\bar{V}_n \leq q) = p$ - Known parameter values.

n	p					
	0.01	0.05	0.1	0.9	0.95	0.99
10	1.18	1.18	1.18	1.28	1.37	1.47
20	1.09	1.09	1.09	1.14	1.14	1.19
50	1.04	1.04	1.04	1.04	1.06	1.06
100	1.02	1.02	1.02	1.02	1.02	1.03
200	1.01	1.01	1.01	1.01	1.01	1.01

Graphical display of the distribution is given in Figure 3.

Theorem 3.1. *Let the Assumption 2.1 hold. The distribution of statistic $\bar{V}_n$ does not change with the change of parameters of the distribution of variable X when the parameters μ and σ of the distribution of variable X are unknown and are estimated with $\bar{X}_n = \frac{1}{n}\sum_{i=1}^{n} X_i$ and $\hat{S}_n^2 = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X}_n)^2$, respectively.*

Proof. Let the distribution of variable X be normal $\mathcal{N}(\mu, \sigma^2)$, where parameters μ and σ^2 are unknown, and let $X_1, \ldots, X_n$ be a random sample of variable X. Then $F_n^*(x) \sim$

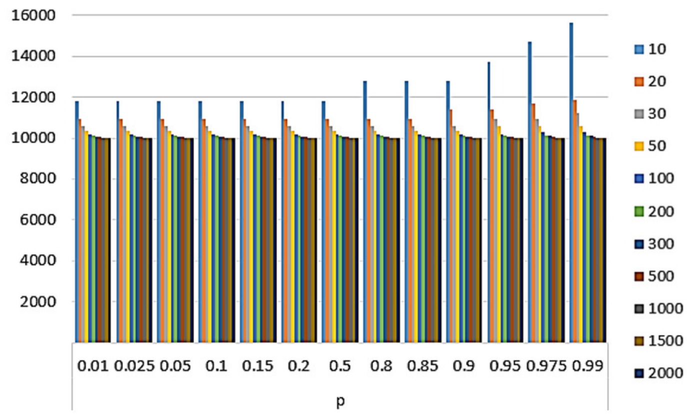

Figure 3. $F_{\bar{V}_n}(q) = P(\bar{V}_n \leq q) = p$ - Known parameter values.

$\mathscr{B}(n, F(x)), x \in \mathbb{R}$ [6]. Let $\hat{\mu} = \bar{X}_n$ and $\hat{\sigma}^2 = \tilde{S}_n^2$ be the estimators, and

$$
\begin{aligned}
I_1(x) &= [F_{\hat{\mu}+\hat{\sigma}}(x), F_{\hat{\mu}-\hat{\sigma}}(x)],\\
I_2(x) &= [F_{\hat{\mu}+1.96\hat{\sigma}}(x), F_{\hat{\mu}+\hat{\sigma}}(x)] \cup (F_{\hat{\mu}-\hat{\sigma}}(x), F_{\hat{\mu}-1.96\hat{\sigma}}(x)],\\
I_3(x) &= [F_{\hat{\mu}+2.58\hat{\sigma}}(x), F_{\hat{\mu}+1.96\hat{\sigma}}(x)] \cup (F_{\hat{\mu}-1.96\hat{\sigma}}(x), F_{\hat{\mu}-2.58\hat{\sigma}}(x)),\\
I_4(x) &= [0, F_{\hat{\mu}+2.58\hat{\sigma}}(x)] \cup (F_{\hat{\mu}-2.58\hat{\sigma}}(x), 1],
\end{aligned}
$$

where $F_{\hat{\mu}\pm h\hat{\sigma}}$, $h \in \{1, 1.96, 2.58, 2.81\}$ are the CDFs of variables with normal distributions with parameters $\hat{\mu} \pm h\hat{\sigma}$ and $\hat{\sigma}$. Then for

$$
q_{\text{zone}_{\hat{\mu},\hat{\sigma}}}(x) = \begin{cases} 1, & x \in I_1(x) \\ 1.96, & x \in I_2(x) \\ 2.58, & x \in I_3(x) \\ 2.81, & x \in I_4(x) \end{cases}, \quad x \in \mathbb{R}.
$$

the sample $q_{\text{zone}_{\hat{\mu},\hat{\sigma}}}(X_j), j = 1, \ldots, n$ is obtained. Further on, let $Z_j = \frac{X_j - \hat{\mu}}{\hat{\sigma}}, j = 1, \ldots, n$, $a_1 = 1, a_2 = 1.96, a_3 = 2.58, a_4 = 2.81$ and

$$
\begin{aligned}
I_1'(z) &= [F_1(z), F_{-1}(z)],\\
I_2'(z) &= [F_{1.96}(z), F_1(z)] \cup (F_{-1}(z), F_{-1.96}(z)],\\
I_3'(z) &= [F_{2.58}(z), F_{1.96}(z)] \cup (F_{-1.96}(z), F_{-2.58}(z)],\\
I_4'(z) &= [0, F_{2.58}(z)] \cup (F_{-2.58}(z), 1].
\end{aligned}
$$

Then,

$$F_{\hat{\mu}\pm h\hat{\sigma}}(X_j) = \frac{1}{\sqrt{2\pi}\hat{\sigma}} \int_{-\infty}^{X_j} e^{-\frac{(t-\hat{\mu}\mp h\hat{\sigma})^2}{2\hat{\sigma}^2}} dt = \left| \begin{matrix} t = \hat{\sigma}z+\hat{\mu} & t \to -\infty & t = X_j \\ dt = \hat{\sigma}dz & z \to -\infty & z = \frac{X_j-\hat{\mu}}{\hat{\sigma}} = Z_j \end{matrix} \right|$$
$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{Z_j} e^{-\frac{(z\mp h)^2}{2}} dz = F_{\mp h}(Z_j), \quad j = 1,\dots,n.$$

Hence, $I_k(X_j) = I'_k(Z_j)$, $k = 1,2,3,4$. Finally, for $j = 1,\dots,n$ and $k = 1,2,3,4$

$$P\left(q_{\text{zone }\hat{\mu},\hat{\sigma}}(X_j) = a_k\right) = P\left(F_n^*(X_j) \in I_k(X_j)\right) = P\left(F_n^*(X_j) \in I'_k(Z_j)\right).$$

Now let the distribution of variable X be normal $N(\mu_2,\sigma_2^2)$, where parameters μ_2 and σ_2^2 are unknown but different from μ_1 and σ_1^2 ($(\mu_1,\sigma_1^2) \neq (\mu_2,\sigma_2^2)$). Analogously, $F_n^*(x) \sim \mathscr{B}(n,F(x))$, and

$$Y_j = \frac{X_j-\hat{\mu}}{\hat{\sigma}}, j = 1,\dots,n$$

satisfies

$$P\left(q_{\text{zone }\hat{\mu},\hat{\sigma}}(X_j) = a_k\right) = P\left(F_n^*(X_j) \in I'_k(Y_j)\right).$$

Since Z_j and Y_j have the same distributions relative to the corresponding X [6] (both are determined with the distribution of X, $\hat{\mu}$ and $\hat{\sigma}$, where $\hat{\mu}$ and $\hat{\sigma}$ are consistent parameters estimators), it follows that the distribution of statistic $q_{\text{zone }\hat{\mu},\hat{\sigma}}(X_j)$, and therefore the distribution of statistic $\bar{V}_n$, is same in both cases. □

Theoretically, when parameters μ and σ^2 are estimated with $\bar{X}_n = \frac{1}{n}\sum_{i=1}^n X_i$ and $\hat{S}_n^2 = \frac{1}{n-1}\sum_{i=1}^n (X_i-\bar{X}_n)^2$, respectively, the distribution of statistic $\bar{V}_n$, as well as its basic properties, remains the same if its distribution does not depend on parameter values. However, empirically, that never happens. Namely, even though the sample is from variable $X \sim N(\mu,\sigma^2)$, $\bar{X}_n = \mu \pm \varepsilon_1$ and $\hat{S}_n^2 = \sigma^2 \pm \varepsilon_2$ will hold almost certainly. Errors ε_1 and ε_2 are then accumulated when calculating the values $q_{\text{zone}}(X_i)$, $i = 1,\dots,n$, i.e., the empirical value of $\bar{V}_n$. Hence, the distribution of $\bar{V}_n$ is slightly changed. Monte Carlo simulations yield the results in Table 2.

Table 2. $F_{\bar{V}_n}(q) = P(\bar{V}_n \leq q) = p$ - Estimated parameter values.

n	p					
	0.01	0.05	0.1	0.9	0.95	0.99
10	1.18	1.18	1.18	1.18	1.18	1.28
20	1.09	1.09	1.09	1.09	1.14	1.19
50	1.04	1.04	1.04	1.04	1.06	1.06
100	1.02	1.02	1.02	1.02	1.02	1.03
200	1.01	1.01	1.01	1.01	1.01	1.01

Graphical display of the distribution is given in Figure 4.

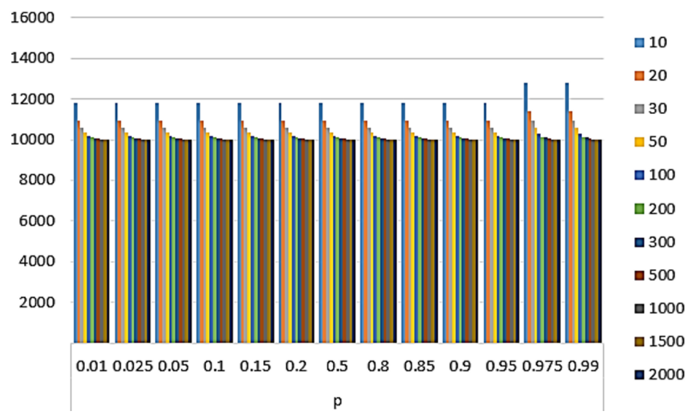

Figure 4. $F_{\bar{V}_n}(q) = P(\bar{V}_n \leq q) = p$ - Estimated parameter values.

The values are smaller when the quantile-zone function is defined with estimated parameters because, for empirically obtained samples, most often the sample mean $\bar{X}_n$ and variance $\tilde{S}_n^2$ are better indicators of the expected value and the dispersion of obtained sample elements than values μ and σ^2 that are used for sample modeling. The difference in distribution is smaller for larger sample sizes. For $n > 500$ the distributions are identical due to estimators being consistent.

4 Conclusions

This paper has immensely helped in understainding quantile-zone test statistic in terms of proper theoretical description. Now it will be much easier to approach improving the definiton of this statistic. That can be done by neglecting the 3σ rule analogy in seting the multiplicators h of σ in $F_{\mu \pm h\sigma}$ so that statistic can perform better in normality testing or goodness of fit testing in general. Also, much more information can be known in terms of attempting to calculate asymptotic power and efficiency.

The future research consists of a modification of the test statistic to avoid a degenerate limiting distribution. In this case, the zone boundaries would probably need to depend on the sample size.

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