Thailand Statistician
April 2025; 23(2): 438-446
http://statassoc.or.th
Contributed paper

Estimation of Population Mean in the Presence of Non-Response for Time-Based Surveys

Sanjay Kumar* [a] and Priyanka Chhaparwal [b]

[a] Department of Statistics, Central University of Rajasthan, Kishangarh, Ajmer, Rajasthan, India.

[b] Department of mathematics, University of Engineering and Management, Jaipur, Rajasthan, India.

*Corresponding author; e-mail: sanjay.kumar@curaj.ac.in

Received: 30 May 2022
Revised: 25 December 2022
Accepted: 4 January 2023

Abstract

An estimate of the location of a distribution is the most fundamental type of inference about a population. Consequently, obtaining more accurate estimators of the population mean of interest is essential in every statistical estimating technique. Survey statisticians most often use priori information at an estimation stage to form an estimator for estimating parameters. In this study, we suggested an estimator for the population mean in the presence of non-response utilizing information from the past surveys along with information available from the current surveys in the form of a hybrid exponentially weighted moving average. We obtained the expressions of the suggested estimator's mean and variance and established the mathematical conditions to demonstrate the efficiency of the suggested estimator. We supported the theoretical outcomes with the help of a simulation study and a real-life example. The results show that the utilization of information from past surveys along with the current surveys improves the efficiency of the suggested estimator. For example: in the simulation study, for a sample size $n(=50,100)$ at the non-response rate $W_2(=0.20,0.15)$ and weights $\alpha_1(0.10)$ and $\alpha_2(0.15)$ to the current and past observations, variances of the suggested estimator were $(0.000683, 0.000559; 0.000635, 0.000309)$, which were less than $(0.020944, 0.009756; 0.020024, 0.008920)$ of the existing Hansen and Hurwitz (1946) estimator. Similarly, in the empirical study of the real-life dataset, for the sample number $\delta(=6)$ having size $n(=12)$ at $W_2(=0.30,0.25), \alpha_1(=0.10)$ and $\alpha_2(=0.15)$, variances of the suggested estimator were $(0.74,\ 0.71)$, which were significantly less than $(95.12, 90.65)$ of the existing Hansen and Hurwitz (1946) estimator. The suggested work is limited to the homogeneous population only.

Keywords: HEWMA, prior information, variance, study variable, simulation study.

1. Introduction

Sample Survey is broadly used in various areas such as demography, economics, engineering, business management, education, engineering, medical sciences, agricultural sciences, and social sciences. The core objective of the survey sampling theory is to make inferences about unknown parameters such as population total, population mean, population proportion, population variance, etc. The most fundamental inference about a population is to estimate the population mean. Other statistical measures, such as variance, standard deviations, and others, can also be calculated with its assistance. Several authors, such as Singh (2003), Hafeez and Shabbir (2015), Sharma and Kumar (2021), Yadav (2022), and others, have worked on the estimation of the population mean.

In real-life situations, almost all surveyors face problems due to non-response. There are two types of non-responses: item non-response and unit non-response. Item non-response implies that the information collected from some units is incomplete. The problem of unit non-response is an error due to not all sampled units provide their information i.e. failure to measure some of the sampled units. In this study, we have considered the problem of unit non-response. We usually face this situation with a survey when respondents are human beings. It occurs due to several reasons-respondents might be busy, uninterested, uncooperative, illiterate, physically or mentally handicapped, or afraid. Hansen and Hurwitz (1946) attempted this situation and suggested that a sub-sample from initial non-respondents is contacted again through a personal interview with an improved and expensive method, suggesting the first attempt by mail questionnaire. Further, several authors, such as Singh (2003), Ahmed et al. (2016), Sharma and Kumar (2020), and others have examined the problem of non-response.

Let us consider a finite population $U:(U_1,U_2,....U_N)$ of size N. Further, it is supposed that the population U is composed of N_1 responding and N_2 non-responding units. Now, let Y be a variable of interest. For estimating the population mean $\mu_Y\left(=\sum_{i=1}^{N}y_i/N\right)$ of the study variable, a sample of size n is selected using simple random sampling without replacement (SRSWOR). Let us consider that in a sample of the size n, n_1 units respond in the first attempt and n_2 units do not and hence are considered as non-respondents. From n_2 non-respondents, a sub-sample of size $r=n_2/k; k>1$ is selected using SRSWOR and measurements are taken from all the r units through personal interviews. It is considered that all the r units respond this time.

Hansen and Hurwitz (1946) suggested an unbiased estimator for the population mean μ_Y of the study variable and is given by

$$\bar{y}^{*}=\gamma_1\bar{y}_1+\gamma_2\bar{y}_{2r}, \tag{1}$$

where $\gamma_1=n_1/n, \bar{y}_1=\sum_{i=1}^{n_1}y_i/n_1$, $\gamma_2=n_2/n$ and $\bar{y}_{2r}=\sum_{i=1}^{r}y_i/r$. The variance of the estimator $\bar{y}^{*}$ is given by

$$Var\left(\bar{y}^{*}\right)=\theta S_Y^2+\frac{W_2\left(k-1\right)}{n}S_{Y(2)}^2, \tag{2}$$

where $\theta=\left(1/n-1/N\right), S_Y^2=\sum_{i=1}^{N}\left(y_i-\mu_Y\right)^2/\left(N-1\right), S_{Y(2)}^2=\sum_{i=1}^{N_2}\left(y_i-\mu_{Y(2)}\right)^2/\left(N_2-1\right)$, and

$\mu_{Y(2)}=\sum_{i=1}^{N_2}y_i/N_2, W_2=N_2/N, \bar{y}_{2r}=\sum_{i=1}^{r}y_i/r.$

We collect information generally from a current survey (say $\bar{y}_{\delta}^{*}$ at time δ) only for estimating parameters. Sometimes, we conduct surveys with respect to a specific time interval such as weekly, monthly or annually. For such time-based surveys, we can improve the performance of estimators if we utilize information from both the current and the past surveys (say $\bar{y}_{\delta-1}^{*}$ at time $\delta-1$, $\bar{y}_{\delta-2}^{*}$ at time $\delta-2$, and so on). Noor-ul-Amin (2020), Chhaparwal and Kumar (2022), and others had studied the population mean estimation for time-based surveys with complete information on all the sampled units. In this study, we suggested an estimator for the population mean in the presence of non-response using information from past and current surveys both. And for this purpose, we used the hybrid exponentially weighted moving average (HEWMA) statistic.

2. Hybrid Exponentially Weighted Moving Average (HEWMA)

Suppose $\{Z_{\delta}\}$ for $\delta \geq 1$ be the sequence of independently and identically normally distributed random variables i.e., $Z_{\delta} \sim IIN(\mu_Y, \sigma^2)$. Now let us define a sequence $\{HE_{\delta}\}$ by using the following formula

$$HE_{\delta} = \alpha_1 E_{\delta} + (1-\alpha_1) HE_{\delta-1}, \quad 0 < \alpha_1 \leq 1,$$

where $E_{\delta} = \alpha_2 \bar{Z}_{\delta} + (1-\alpha_2) E_{\delta-1}$, $0 < \alpha_2 \leq 1, \delta \geq 1$, the subscripts δ and $\delta-1$ are the sample numbers having the sample size n, and α_1 and α_2 are constants.

Haq (2013) suggested the statistic HE_{δ} known as an HEWMA statistic which requires EWMA statistic E_{δ}. The initial values of E_{δ} and HE_{δ} are taken as expected mean and can be made available from a pilot survey. Haq (2017) studied that

$$E(HE_{\delta}) = \mu_Y,$$

and

$$Var(HE_{\delta}) = \left(\frac{\alpha_1\alpha_2}{\alpha_1-\alpha_2}\right)^2 \left[\frac{(1-\alpha_1)^2\left\{1-(1-\alpha_1)^{2\delta}\right\}}{1-(1-\alpha_1)^2} + \frac{(1-\alpha_2)^2\left\{1-(1-\alpha_2)^{2\delta}\right\}}{1-(1-\alpha_2)^2} - \frac{2(1-\alpha_1)(1-\alpha_2)\left\{1-(1-\alpha_1)^{\delta}(1-\alpha_2)^{\delta}\right\}}{1-(1-\alpha_1)(1-\alpha_2)}\right]\frac{\sigma^2}{n} = \alpha_{\delta}^{*}\frac{\sigma^2}{n},$$

where

$$\alpha_{\delta}^{*} = \left(\frac{\alpha_1\alpha_2}{\alpha_1-\alpha_2}\right)^2 \left[\frac{(1-\alpha_1)^2\left\{1-(1-\alpha_1)^{2\delta}\right\}}{1-(1-\alpha_1)^2} + \frac{(1-\alpha_2)^2\left\{1-(1-\alpha_2)^{2\delta}\right\}}{1-(1-\alpha_2)^2} - \frac{2(1-\alpha_1)(1-\alpha_2)\left\{1-(1-\alpha_1)^{\delta}(1-\alpha_2)^{\delta}\right\}}{1-(1-\alpha_1)(1-\alpha_2)}\right]\frac{\sigma^2}{n}.$$

3. Proposed Estimator

Motivated from Haq (2013, 2017) and Hansen and Hurwitz (1946), we suggest an HEWMA estimator for the variable of interest Y in the presence of non-response as

$$S_\delta^* = \alpha_1 E_{\delta y}^* + (1-\alpha_1) S_{\delta-1}^*, \quad 0 < \alpha_1 \le 1, \tag{3}$$

where,

$$E_{\delta y}^* = \alpha_2 \bar{y}_\delta^* + (1-\alpha_2) E_{\delta y-1}^*, \quad 0 < \alpha_2 \le 1. \tag{4}$$

Here, the initial values for $E_{\delta y}^*$ and S_δ^* are taken as expected mean and can be obtained from the information available or from a pilot survey.

After repeated substitution, (3) and (4) can be written in the forms as

$$S_\delta^* = \alpha_1 \sum_{i=1}^{\delta-1} (1-\alpha_1)^i E_{\delta y-1}^* + (1-\alpha_1)^\delta S_0^*, \tag{5}$$

and

$$E_{\delta y}^* = \alpha_2 \sum_{j=0}^{\delta-1} (1-\alpha_2)^j \bar{y}_{\delta-j}^* + (1-\alpha_2)^\delta E_{0y-1}^*. \tag{6}$$

Now, putting (6) in (5), we obtain

$$\begin{aligned} S_\delta^* &= \alpha_1\alpha_2 \sum_{i=0}^{\delta-1} (1-\alpha_1)^i \sum_{j=0}^{\delta-i-1} (1-\alpha_2)^j \bar{y}_{\delta-i-j}^* + \alpha_1 \sum_{i=0}^{\delta-1} (1-\alpha_1)^i (1-\alpha_2)^{\delta-i} \mu_Y + (1-\alpha_1)^\delta \mu_Y, \\ &= \alpha_1\alpha_2 \sum_{i=1}^{\delta} \left\{ (1-\alpha_2)^{\delta-i} \sum_{j=0}^{\delta-i} \left(\frac{1-\alpha_1}{1-\alpha_2} \right)^j \right\} \bar{y}_i^* + \alpha_1 \sum_{i=0}^{\delta-1} (1-\alpha_1)^i (1-\alpha_2)^{\delta-i} \mu_Y + (1-\alpha_1)^\delta \mu_Y. \end{aligned} \tag{7}$$

Taking expectations from both sides of (7), we obtain,

$$\begin{aligned} E(S_\delta^*) &= \alpha_1\alpha_2 \sum_{i=1}^{\delta} \left\{ (1-\alpha_2)^{\delta-i} \sum_{j=0}^{\delta-i} \left(\frac{1-\alpha_1}{1-\alpha_2} \right)^j \right\} E(\bar{y}_i^*) + \alpha_1 \sum_{i=0}^{\delta-1} (1-\alpha_1)^i (1-\alpha_2)^{\delta-i} \mu_Y + (1-\alpha_1)^\delta \mu_Y, \\ &= \alpha_1\alpha_2 \sum_{i=1}^{\delta} \left\{ (1-\alpha_2)^{\delta-i} \sum_{j=0}^{\delta-i} \left(\frac{1-\alpha_1}{1-\alpha_2} \right)^j \right\} \mu_Y + \alpha_1 \sum_{i=0}^{\delta-1} (1-\alpha_1)^i (1-\alpha_2)^{\delta-i} \mu_Y + (1-\alpha_1)^\delta \mu_Y. \end{aligned} \tag{8}$$

On simplification of (8), we obtain,

$$E(S_\delta^*) = \mu_Y. \tag{9}$$

Further, taking the variance of (7), we obtain,

$$\begin{aligned} Var(S_\delta^*) &= \alpha_1\alpha_2 \sum_{i=1}^{\delta} \left\{ (1-\alpha_2)^{\delta-i} \sum_{j=0}^{\delta-i} \left(\frac{1-\alpha_1}{1-\alpha_2} \right)^j \right\} Var(\bar{y}_i^*), \\ &= \left(\frac{\alpha_1\alpha_2}{\alpha_1-\alpha_2} \right)^2 \left[\sum_{i=1}^{2} \frac{(1-\alpha_i)^2 \left\{ 1-(1-\alpha_i)^{2\delta} \right\}}{1-(1-\alpha_i)^2} - \frac{2(1-\alpha_1)(1-\alpha_2)\left\{ 1-(1-\alpha_1)^\delta (1-\alpha_2)^\delta \right\}}{1-(1-\alpha_1)(1-\alpha_2)} \right] Var(\bar{y}_i^*), \\ &= \alpha_\delta^* \left[\theta S_Y^2 + \frac{W_2(k-1)}{n} S_{Y(2)}^2 \right]. \end{aligned} \tag{10}$$

Note: For $\alpha_1 = 1$ and $\alpha_2 = 1$, the suggested estimator S_δ^* reduces to the estimator $\bar{y}^*$.

4. Mathematical Comparison

In this section, we obtained a mathematical condition under which the performance of the suggested estimator S_δ^* is better than that of the existing estimator $\bar{y}^*$.

$$Var\left(S_\delta^*\right) < Var\left(\bar{y}^*\right) \text{ if } 0 < \alpha_\delta^* < 1, \tag{11}$$

which is always true as the values of α_1 and α_2 range from 0 and 1. The suggested estimator S_δ^* is preferred over the estimator $\bar{y}^*$ only when the condition given in (11) is satisfied.

5. Simulation Study

In this section, we demonstrate the performance of the suggested estimator through the Monte-Carlo simulation approach using R software (R-4.1.2). For this purpose, we generate a population of size from the normal distribution with assumed parameters as $Y \sim N(0,1)$. For calculating the variance of the suggested estimator in (3), we select $M = 51000$ random samples of size $n(=50,100)$ from all the possible $\binom{500}{n}$ samples by using SRSWOR method of sampling. Thus, the value of is from 1 to M. We calculate S_δ^* for each of the $M = 51000$ samples. Here, we consider the non-response rate as 20% and 15% and take these as the last 20% and 15% units from each sample. Further, we consider the value of $k = 2.0$. The overall performance of the suggested estimator is assessed for different choices of $\alpha_2(=0.15,0.50,0.9999)$ by fixing $\alpha_1 = 0.10$ as well as for different choices of $\alpha_1(=0.10,0.25,0.999)$ by fixing $\alpha_2 = 0.9999$.

We obtain the simulated values of variance (Var.) and percent relative efficiency (PRE) as follows:

$$Var(T) = \frac{1}{M}\sum_{j=1}^{M}\left(T_j - \mu_Y\right)^2 \text{ and } PRE(T) = \frac{Var\left(\bar{y}^*\right)}{Var(T)} * 100, \tag{12}$$

where $T = \bar{y}^*$ and S_δ^*.

Table 1 Simulated values of variances and PREs of the estimators at different values of α_2 and n for the fix value of $\alpha_1 = 0.10$

	$W_2 = 0.20$				$W_2 = 0.15$			
	$n = 50$		$n = 100$		$n = 50$		$n = 100$	
Est.	Var	PRE	Var	PRE	Var	PRE	Var	PRE
				$\alpha_2 = 0.15$				
$\bar{y}^*$	0.020944	100.00	0.009756	100.00	0.020024	100.00	0.008920	100.00
S_δ^*	0.000683	3066.47	0.000559	1745.26	0.000635	3153.39	0.000309	2886.73
				$\alpha_2 = 0.50$				
$\bar{y}^*$	0.020944	100.00	0.009756	100.00	0.020024	100.00	0.008920	100.00
S_δ^*	0.000975	2148.10	0.000696	1401.72	0.000919	2178.89	0.000438	2036.53
				$\alpha_2 = 0.9999 \cong 1.0$				
$\bar{y}^*$	0.020944	100.00	0.009756	100.00	0.020024	100.00	0.008920	100.00
S_δ^*	0.001108	1890.25	0.000757	1288.77	0.001046	1914.34	0.000495	1802.02

Table 2 Simulated values of variances and PREs of the estimators at different values of α_1 and n for the fix value of $\alpha_2 = 0.9999 \cong 1.0$

	$W_2 = 0.20$				$W_2 = 0.15$			
	$n = 50$		$n = 100$		$n = 50$		$n = 100$	
Est.	Var	PRE	Var	PRE	Var	PRE	Var	PRE
				$\alpha_1 = 0.10$				
$\bar{y}^*$	0.020944	100.00	0.009756	100.00	0.020024	100.00	0.008920	100.00
S_δ^*	0.001108	1890.25	0.000757	1288.77	0.001046	1914.34	0.000495	1802.02
				$\alpha_1 = 0.25$				
$\bar{y}^*$	0.020944	100.00	0.009756	100.00	0.020024	100.00	0.008920	100.00
S_δ^*	0.002983	702.11	0.001619	602.59	0.002852	702.10	0.001302	685.10
				$\alpha_1 = 0.999 \cong 1.0$				
$\bar{y}^*$	0.020944	100.00	0.009756	100.00	0.020024	100.00	0.008920	100.00
S_δ^*	0.020898	100.22	0.009735	100.22	0.019980	100.22	0.008901	100.21

From the Tables 1 and 2, we can observe that the variance of the suggested estimator is smaller than that of the Hansen and Hurwitz estimator $\bar{y}^*$. Thus, the suggested estimator is higher in efficiency in comparison to the existing estimator $\bar{y}^*$. It can also be observed that the variance of the estimator is reduced with the increased information. The values of weights α_1 and α_2 assigned respectively to the current and the past observations show the performance of the suggested estimator in terms of variance and PRE. The variance of the suggested estimator is increased with the increased values of α_1 and α_2. Also, the variances of the estimators are reduced with the decreased value of non-response rate in the sample. Further, from Table 2, it is observed that when $\alpha_1 \to 1$ and $\alpha_2 \to 1$, the variance of the suggested estimator S_δ^* approaches to that of the estimator $\bar{y}^*$ as discussed in the Section 3.

6. An Application to a Real Data Set

In this section, we take a real-life example from "Pocket book of Agricultural Statistics, 2017" issued by Ministry of Agriculture & Farmers Welfare, India (http://www.indiaenvironmentportal.org.in). In the dataset, we consider the Wholesale Price Index (2011-2012 to 2016-2017, Base: 2004-2005=100) of oilseeds as the variable of interest to prove the use of the suggested estimator. The population has 17 types of oilseeds with $\mu_Y = 181.96$. We randomly select 12 oilseeds from 2011-12 to 2016-17 from the population by SRSWOR. Here, we consider the non-response rate as 30% and 25% and we take these as the last 30% and 25% units from each of the six samples $(\delta = 1,2,\ldots,6)$. Further, we consider the value of $k = 2.0$. The overall performance of the suggested estimator is assessed for different choices of $\alpha_2 (= 0.15, 0.50, 0.9999)$ by fixing $\alpha_1 = 0.10$ as well as for different choices of $\alpha_1 (= 0.10, 0.25, 0.999)$ by fixing $\alpha_2 = 0.9999$. We obtain values of $\bar{y}^*, S_\delta^*, V(\bar{y}^*)$ and $V(S_\delta^*)$ using (1), (3), (2) and (10), respectively. These computed values are presented in Tables 3 and 4 which show that the suggested estimator S_δ^* has less variance than the existing estimator $\bar{y}^*$ and hence the suggested estimator is more efficient than the existing estimator

$\bar{y}^*$. The variance of the suggested estimator is increased with the increased values of α_1 and α_2. Also, the variances of the estimators are reduced with the decreased value of non-response rate in the sample. Further, when $\alpha_1 \to 1$ and $\alpha_2 \to 1$, it is observed from Table 4 that the variance of the suggested estimator S_δ^* approaches to that of the estimator $\bar{y}^*$.

Table 3 Computations of values of $\bar{y}^*, S_\delta^*, Var\left(\bar{y}_\delta^*\right)$ and $Var\left(S_\delta^*\right)$ for various values of α_2 with fixed value of $\alpha_1 = 0.10$.

	$W_2 = 0.30$				$W_2 = 0.25$			
δ	$\bar{y}^*$	S_δ^*	$Var\left(\bar{y}_\delta^*\right)$	$Var\left(S_\delta^*\right)$	$\bar{y}^*$	S_δ^*	$Var\left(\bar{y}_\delta^*\right)$	$Var\left(S_\delta^*\right)$
				$\alpha_2 = 0.15$				
1	208.99	220.14	95.12	0.02	216.98	225.70	90.65	0.02
2	248.51	231.38	95.12	0.09	261.58	238.68	90.65	0.08
3	264.40	238.71	95.12	0.20	275.23	247.16	90.65	0.19
4	272.55	220.14	95.12	0.35	279.65	225.70	90.65	0.34
5	264.54	231.38	95.12	0.54	273.33	238.68	90.65	0.51
6	263.42	238.71	95.12	0.74	277.47	247.16	90.65	0.71
				$\alpha_2 = 0.50$				
1	208.99	222.15	95.12	0.24	216.98	228.08	90.65	0.23
2	248.51	232.20	95.12	0.70	261.58	239.87	90.65	0.67
3	264.40	239.69	95.12	1.25	275.23	248.61	90.65	1.19
4	272.55	222.15	95.12	1.77	279.65	228.08	90.65	1.69
5	264.54	232.20	95.12	2.23	273.33	239.87	90.65	2.13
6	263.42	239.69	95.12	2.63	277.47	248.61	90.65	2.51
				$\alpha_2 = 0.9999 \cong 1.0$				
1	208.99	224.32	95.12	0.95	216.98	230.61	90.65	0.91
2	248.51	234.18	95.12	1.72	261.58	242.18	90.65	1.64
3	264.40	242.16	95.12	2.35	275.23	251.27	90.65	2.24
4	272.55	224.32	95.12	2.85	279.65	230.61	90.65	2.72
5	264.54	234.18	95.12	3.26	273.33	242.18	90.65	3.11
6	263.42	242.16	95.12	3.59	277.47	251.27	90.65	3.42

Table 4 Computations of exact values of $\bar{y}^*, S_\delta^*, Var\left(\bar{y}_\delta^*\right)$ and $Var\left(S_\delta^*\right)$ for various values of α_1 with fixed value of $\alpha_2 = 0.9999 \cong 1.0$.

	$W_2 = 0.30$				$W_2 = 0.25$			
	$\bar{y}^*$	S_δ^*	$Var\left(\bar{y}_\delta^*\right)$	$Var\left(S_\delta^*\right)$	$\bar{y}^*$	S_δ^*	$Var\left(\bar{y}_\delta^*\right)$	$Var\left(S_\delta^*\right)$
δ				$\alpha_1 = 0.10$				
1	208.99	224.32	95.12	0.95	216.98	230.61	90.65	0.91
2	248.51	234.18	95.12	1.72	261.58	242.18	90.65	1.64
3	264.40	242.16	95.12	2.35	275.23	251.27	90.65	2.24
4	272.55	224.32	95.12	2.85	279.65	230.61	90.65	2.72
5	264.54	234.18	95.12	3.26	273.33	242.18	90.65	3.11
6	263.42	242.16	95.12	3.59	277.47	251.27	90.65	3.42
				$\alpha_1 = 0.25$				
1	208.99	238.47	95.12	5.94	216.98	246.93	90.65	5.66
2	248.51	244.02	95.12	9.29	261.58	253.86	90.65	8.85
3	264.40	249.69	95.12	11.17	275.23	260.17	90.65	10.64
4	272.55	238.47	95.12	12.23	279.65	246.93	90.65	11.65
5	264.54	244.02	95.12	12.82	273.33	253.86	90.65	12.22
6	263.42	249.69	95.12	13.16	277.47	260.17	90.65	12.54
				$\alpha_1 = 0.999 \cong 1.0$				
1	208.99	243.86	95.12	94.91	216.98	253.35	90.65	90.45
2	248.51	252.01	95.12	94.91	261.58	262.92	90.65	90.45
3	264.40	264.38	95.12	94.91	275.23	275.22	90.65	90.45
4	272.55	243.86	95.12	94.91	279.65	253.35	90.65	90.45
5	264.54	252.01	95.12	94.91	273.33	262.92	90.65	90.45
6	263.42	264.38	95.12	94.91	277.47	275.22	90.65	90.45

7. Conclusions

Statisticians often utilize priori information at an estimation stage to excel the performance of an estimator. In this article, we suggested an estimator in the presence of non-response using HEWMA statistics, which utilizes past and current survey information. The results obtained through the simulation study with a generated dataset and the empirical study with a real-life dataset show that the suggested estimator has less variance than the existing estimator; hence, it is found more efficient estimator than the existing estimator. Further, it is observed that the variance of the suggested estimator is reduced with the increased information. The variance of the estimator is also reduced with the decreased value of the non-response rate in the sample. The variance of the suggested estimator is increased with the increased values of the weights to the current and past observations. When these weights equalize to one, the suggested estimator is reduced to the existing Hansen and Hurwitz estimator. The suggested work is limited to the homogeneous population only. This work can be improved by using other sampling designs.

Acknowledgments

We thank the Editor and reviewers for their thorough reviews and highly appreciate the comments and suggestions, which significantly improved the quality of the paper.

References

Ahmed S, Shabbir J, Hafeez W. Hansen and Hurwitz estimator with scrambled response on second call in stratified random sampling. J Stat Appl Probab. 2016; 5(2): 357-369.

Chhaparwal P, Kumar S. Improving efficiencies of ratio- and product-type estimators for estimating population mean for time-based survey**.** Journal of Reliability and Statistical Studies. 2022; 15*(1):* 325–340.

Hafeez W, Shabbir J. Estimation of the finite population mean, using median based estimators in stratified random sampling. J Stat Appl Pro. 2015; 4(3): 367-374.

Hansen MH, Hurwitz WN. The problem of non-response in sample surveys. J Amer Stat Assoc. 1946; 41**(**236**):** 517-529.

Haq A. A new hybrid exponentially weighted moving average control chart for monitoring process mean. Qual Reliab Eng Int. 2013; 29(7): 1015-1025.

Haq A. A new hybrid exponentially weighted moving average control chart for monitoring process mean: discussion. Qual Reliab Eng Int. 2017; 33(7): 1629-1631.

Noor-ul-Amin M. Memory type ratio and product estimators for population mean for time-based surveys. J Stat Comput Simul. 2020; 90(17): 3080–3092.

Sharma V, Kumar S. Estimation of population mean using transformed auxiliary variable and non-response. Investigación Operacional. 2020; 41(3): 438-444.

Sharma V, Kumar S. Class of ratio-cum-product type estimator under double sampling: A simulation study. Thail Stat. 2021; 19(4): 734-742.

Singh S. Advanced sampling theory with applications. Dordrecht: Springer Dordrecht; 2003.

Yadav SK. Modified searls predictive estimation of population mean using known auxiliary character. Thail Stat. 2022; 20(1): 53-65.