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Quality Quandaries: On the Application of Different Ranked Set Sampling Schemes

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INTRODUCTION

Sampling methods play a vital role in all kinds of disciplines, such as medical sciences, engineering, education, and industrial processes. In order to obtain representative sampling units, we rely on the choice of an adequate sampling mechanism. A commonly used method of selection is simple random sampling (SRS). One may think of alternative sampling schemes when some extra information is available about the study variable. In such situations we need an easy-to-measure and/or cheap covariate that helps selecting an appropriate sample before the actual measurements are taken.

McIntyre (1952) introduced ranked set sampling as an alternative to SRS. He noted that ranked set sampling is cost-efficient compared to SRS. He proposed to use a visual inspection (judgment) in ranking the variable of interest before making the actual measurement. For example, in the medical field, a diagnostic blood test to determine the level of serum bilirubin can be decided by visual examination of the eyes (sclera) first. There are different ranked set sampling mechanisms available in the literature in the form of single- and double-ranked set schemes (cf. Dang et al. 2013; Dell and Clutter 1972; Ganeslingam and Ganesh 2006; Stokes 1977; and references therein). The single schemes include ranked set sampling (RSS), median-ranked set sampling (MRSS), percentile-ranked set sampling (PRSS), and extreme-ranked set sampling (ERSS). On similar lines, the double schemes may be obtained in the form of double-ranked set sampling (DRSS), double median-ranked set sampling (DMRSS), median double-ranked set sampling (MDRSS), percentile double-ranked set sampling (PDRSS), double percentile-ranked set sampling (DPRSS), double extreme-ranked set sampling (DERSS), and extreme double-ranked set sampling (EDRSS).

This column is planned for practitioners who want to become familiar with different ranked set strategies to collect sample data. The methods will be illustrated by showing an application to an industrial process. The next section provides the procedures of different sampling strategies for collecting samples from an ongoing process; then we show the application of ranked set–based process monitoring using a dispersion control chart.

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RANKED SET SAMPLING STRATEGIES

This section describes the procedure of different ranked set sampling schemes to collect the data on our variable of interest. The schemes include

FIGURE 1 Filling bottles in a production line.

single and double sampling methodologies. We provide single ranked set schemes in more detail and the double schemes are presented briefly as extended versions of single schemes. For illustration purposes we focus on collecting r random samples (cycles) of size n. We describe the procedure by considering a production line to investigate the amount of filled water (cf. Figure 1).

Single-Ranked Set Strategies

The selection steps for the different single-ranked set sampling schemes are described in the following sections.

Ranked Set Sampling

Step 1: Select n^2 bottles at random from the production line.
Step 2: Divide them randomly into n sets of bottles, each of size n.
Step 3: By visual inspection, arrange them from the smallest to the largest with respect to the level of water.
Step 4: In order to select a ranked set sample of size n, select the bottle from the first set that contains the smallest amount of water; similarly, select the bottle from the second set containing the second smallest amount of water and continue in this fashion until the largest ranked bottle is selected from the last set. This selection leads to an RSS of size n.

The above-mentioned procedure is applied to the production line for selecting an RSS of size 3 and is shown in Figures 2 and 3.

Median-Ranked Set Sampling and Percentile-Ranked Set Sampling

For the selection of MRSS and PRSS we have the same steps 1, 2, and 3 as in RSS. However, at step 4 we select the bottles for the actual measurement differently. In MRSS, the selection of the bottles depends on n. If the sample size is odd, then from

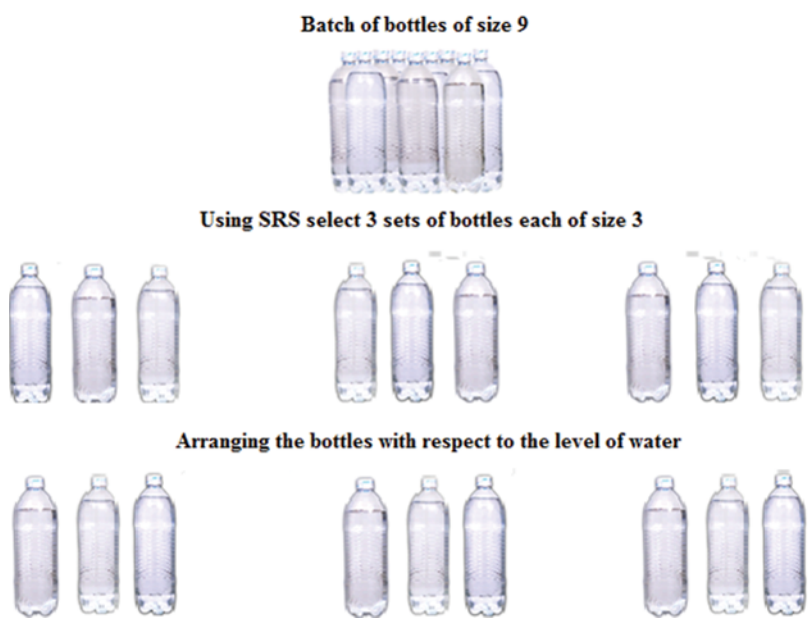

FIGURE 2 Arrangement of bottles for ranked set sampling.

FIGURE 3 Selection of the ranked set sample.

each set select the bottle at the middle (median) position. If the sample size is even, select the $(\frac{n}{2})th$ largest ranked bottle from the first half sets of bottles and the $(\frac{n+2}{2})th$ smallest ranked bottle from the second half of the sets. This results into an MRSS of size n bottles (on which we take the actual measurements). Similarly, if we select a particular percentile (e.g., 75th percentile) from each set of bottles then it results in a PRSS of size n units (on which the actual measurements are taken).

As an extra illustration, we show the selection mechanism of MRSS in case of a sample size $n=3$ (see Figure 4).

Extreme-Ranked Set Sampling

In the selection of ERSS all steps of RSS remain the same, except step 4, where we make the selection of bottles for the actual measurements. The selection of bottles at step 4 depends on the sample size n. In case n is odd, we select the smallest water-filled bottles from the first $\frac{(n-1)}{2}$ sets of bottles, the largest water-filled bottles from the other $\frac{(n-1)}{2}$ sets, and the bottle at the median position from the remaining set. In case n is even, we select the smallest water-filled bottles from the first $\frac{n}{2}$ sets and the largest water-filled bottles from the other $\frac{n}{2}$ sets. In this way, we obtain an ERSS of size n bottles (on which we take the actual measurements). In case n is less than or equal to 3, ERSS and RSS appear similar.

Once we have selected a sample of n bottles, the next step is to perform the actual measurement of water inside the bottles, which have been selected using any of the above mentioned strategies. The measurements are made with the help of a measuring device (in our example a measuring cup). For the sample values obtained by a specific sampling scheme we may compute sample statistics, like the mean $(\bar{X})$ or the standard deviation (S).

We discuss here the computations only for MRSS with r cycles (random samples) of size n, while the other sampling schemes may be dealt on the similar lines. Let $X_{(1,m)j}$, $X_{(2,m)j}$, $\ldots$, $X_{(n,m)j}$ be the first, second, …, and nth measured observations of the amount of water inside the bottles in cycle j under MRSS. Then the estimators for location and dispersion under MRSS for cycle j are defined as

$$\bar{X}_{mrss,j} = \frac{1}{n}\sum_{i=1}^{n} X_{(i,m)j} \quad and$$

$$S_{mrss,j} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(X_{(i,m)j} - \bar{X}_{mrss,j}\right)^2} \quad ;$$

$$j = 1, 2, 3, \ldots, r.$$

The above-mentioned procedure holds for all r cycles (say $r=40$) using the given sampling strategy (in this example, MRSS). In this way, we obtain r samples of size n along with their actual measurements (cf. Figure 5 with $r=40$ and $n=3$).

Double-Ranked Set Strategies

We briefly provide here the selection steps for the different double ranked set sampling schemes following the lines of single ranked set schemes. The initial step is to select at random n^3 bottles from the production line and divide them randomly in n sets each of size n^2.

FIGURE 4 Selection of the median-ranked set sample of size $n=3$.

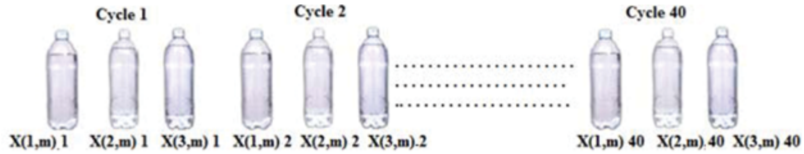

FIGURE 5 Forty cycles of a median-ranked set sample of size 3.

Double-Ranked Set Sampling

The procedure of DRSS is given as follows: First apply steps 1–4 of RSS on the n^2 bottles to obtain a set of n RSS bottles; then apply steps 1–4 again on the n sets of n RSS bottles. This results into a DRSS random sample of size n.

Double Median-Ranked Set Sampling, Double Percentile-Ranked Set Sampling, and Double Extreme-Ranked Set Sampling

The procedure to obtain DMRSS is given as follows: apply MRSS on the n^2 bottles to obtain n MRSS bottles and then apply MRSS again on the n sets of n MRSS bottles. This results in a DMRSS random sample of size n. By replacing the role of MRSS in these steps by PRSS and ERSS we may obtain DPRSS and DERSS, respectively.

Median Double-Ranked Set Sampling, Percentile Double-Ranked Set Sampling, and Extreme Double-Ranked Set Sampling

The procedure to obtain MDRSS is given as follows: apply RSS on the n^2 bottles and then apply MRSS on the n sets of n RSS bottles. This results in an MDRSS random sample of size n. By replacing the role of MRSS by PRSS and ERSS we may obtain PDRSS and EDRSS, respectively.

In continuation of our aforementioned illustrations for single-ranked set strategies (RSS, MRSS, PRSS, ERSS) we may apply the same statistics for the double-ranked set schemes.

Process Monitoring Using Control Charts Based on Ranked Set Sampling

Mehmood et al. (2013) developed Shewhart-type control charts for location under a variety of sampling strategies and runs rules. They reported that control charts based on PRSS, MRSS, DMRSS, and MDRSS perform better compared to the other sampling strategies. Some recent studies in this direction are from Abujiya, Lee, and Riaz (2013) and Abujiya, Riaz, and Lee (2013) and references therein. The main focus had been mainly on monitoring the location using ranked set schemes. It is hard to find literature for monitoring the dispersion parameter under different sampling strategies.

We propose and investigate here the runs rules–based control charting structures for monitoring the dispersion parameter of an ongoing process using different single- and double-ranked set sampling strategies. The choice of some selective sampling strategies and runs rules is based on Riaz et al. (2011) and Mehmood et al. (2013). For the selection of some useful dispersion estimators we have followed Schoonhoven et al. (2011) and Abbasi and Miller (2012). The specific choices of runs rules schemes are based on $(k-m)$ observations out of

TABLE 1 Unbiasing Constants for Different Ranked Set Based Control Charts for Dispersion

		n		
Estimators	*T*	3	5	7
S	MRSS	0.587294	0.50666	0.503195
	DMRSS	0.402284	0.269179	0.201978
	MDRSS	0.475324	0.353591	0.28406
	PRSS	0.587294	0.528242	0.520841
R	MRSS	1.122936	1.255697	1.249905
	DMRSS	0.768142	0.667043	0.57082
	MDRSS	0.907213	0.876189	0.807635
	PRSS	1.122936	1.303291	1.290915
GINI	MRSS	0.748624	0.607552	0.603944
	DMRSS	0.512094	0.322611	0.237767
	MDRSS	0.604808	0.424845	0.33438
	PRSS	0.748624	0.63595	0.624706
MAD	MRSS	0.477081	0.334965	0.331841
	DMRSS	0.324713	0.178366	0.138503
	MDRSS	0.383074	0.236397	0.192355
	PRSS	0.477081	0.358623	0.346055
Q_n	MRSS	0.685029	0.630319	0.644871
	DMRSS	0.457703	0.339278	0.248331
	MDRSS	0.537718	0.452577	0.350238
	PRSS	0.685029	0.680407	0.664015

TABLE 2 Coefficients for the Control Limits for Different Ranked Set–Based Control Charts for Dispersion

		Rules					
T	*n*	1/1	2/3	2/4	9/9	8/9	7/9
S control chart							
SRS	3	2.426114	1.869815	1.95978	0.807903	0.981179	1.127429
	5	2.014701	1.632453	1.694764	0.901566	1.023548	1.127353
	7	1.833589	1.525105	1.578491	0.930414	1.029783	1.118435
MRSS	3	1.639066	1.254818	1.314961	0.542064	0.655967	0.756024
	5	1.08028	0.876366	0.909398	0.480934	0.546805	0.603607
	7	0.846535	0.704878	0.725479	0.4275	0.47369	0.515492
PRSS	3	1.626091	1.257028	1.330434	0.541913	0.653237	0.752851
	5	1.151467	0.906246	0.949703	0.504033	0.572064	0.631567
	7	0.931499	0.779682	0.806484	0.475335	0.524046	0.569714
DMRSS	3	1.063584	0.831122	0.872295	0.361943	0.438342	0.504639
	5	0.582101	0.467182	0.486723	0.255766	0.290753	0.320596
	7	0.383407	0.318327	0.32877	0.195527	0.216315	0.233884
MDRSS	3	1.292854	0.988498	1.036337	0.425987	0.514524	0.592456
	5	0.748339	0.605113	0.629014	0.332364	0.377706	0.416803
	7	0.528361	0.443053	0.455029	0.270304	0.299947	0.324555
R control chart							
SRS	3	4.678728	3.589124	3.758636	1.543645	1.871487	2.152351
	5	5.123276	4.103021	4.263338	2.220161	2.527456	2.793186
	7	5.332807	4.38031	4.527799	2.591169	2.889436	3.148586
MRSS	3	3.158797	2.404765	2.521543	1.03413	1.251874	1.443686
	5	2.747852	2.20322	2.28888	1.184893	1.35022	1.494579
	7	2.529116	2.055752	2.125258	1.194741	1.32888	1.449113
PRSS	3	3.162143	2.409738	2.543316	1.036136	1.252062	1.436829
	5	2.984868	2.285275	2.391052	1.241313	1.409332	1.562118
	7	2.803513	2.247956	2.321606	1.332167	1.478185	1.608986
DMRSS	3	2.060233	1.591351	1.676478	0.690976	0.834416	0.964793
	5	1.482409	1.176843	1.228014	0.629446	0.7172	0.794714
	7	1.120312	0.922984	0.953591	0.547352	0.610102	0.659853
MDRSS	3	2.487341	1.89696	1.988096	0.812176	0.982452	1.132025
	5	1.904572	1.52226	1.586825	0.81921	0.934222	1.033182
	7	1.548634	1.269856	1.316771	0.758064	0.84506	0.916649
GINI control chart							
SRS	3	4.678728	3.589124	3.758636	1.543645	1.871487	2.152351
	5	2.435547	1.970255	2.045176	1.080731	1.228175	1.354072
	7	2.188427	1.807362	1.87496	1.091347	1.213625	1.315705
MRSS	3	2.105865	1.603176	1.681029	0.68942	0.834582	0.962458
	5	1.307214	1.056181	1.096516	0.57641	0.655979	0.7246
	7	1.018051	0.829211	0.855726	0.502381	0.557723	0.60666
PRSS	3	2.108095	1.606492	1.695544	0.690757	0.834708	0.957886
	5	1.387182	1.090238	1.137445	0.602196	0.686242	0.75645
	7	1.091721	0.921443	0.95151	0.556548	0.618208	0.66965
DMRSS	3	1.373489	1.060901	1.117652	0.460651	0.556277	0.643196
	5	0.710417	0.563534	0.584639	0.307266	0.348543	0.38457
	7	0.459317	0.374683	0.386308	0.230022	0.25452	0.275348
MDRSS	3	1.658227	1.26464	1.325397	0.541451	0.654968	0.754684
	5	0.909844	0.729783	0.759388	0.398283	0.452879	0.500392
	7	0.622154	0.52451	0.540534	0.318044	0.35235	0.382831
MAD control chart							
SRS	3	2.151564	1.583501	1.680621	0.648102	0.783239	0.908775
	5	1.692503	1.309199	1.37771	0.576356	0.682515	0.780136

(*Continued*)

TABLE 2 Continued

T	n	Rules 1/1	2/3	2/4	9/9	8/9	7/9
	7	1.611717	1.243116	1.305914	0.618122	0.715412	0.805331
MRSS	3	1.433517	1.057412	1.115298	0.42921	0.523486	0.608224
	5	0.90214	0.685889	0.719506	0.306728	0.364322	0.416264
	7	0.712841	0.572156	0.593963	0.287035	0.331482	0.37214
PRSS	3	1.459251	1.072819	1.118774	0.426448	0.526275	0.607975
	5	0.938814	0.711453	0.743337	0.322499	0.38239	0.435426
	7	0.808612	0.63207	0.659108	0.315371	0.365548	0.409602
DMRSS	3	0.957138	0.703597	0.740901	0.287338	0.350093	0.408264
	5	0.494138	0.364995	0.382277	0.164517	0.195509	0.222007
	7	0.323935	0.25811	0.268393	0.130998	0.150903	0.169448
MDRSS	3	1.125193	0.83178	0.87919	0.336766	0.410666	0.477334
	5	0.626004	0.474584	0.498044	0.211883	0.251811	0.286991
	7	0.457543	0.360735	0.373874	0.181337	0.208886	0.23478
Q_n control chart							
SRS	3	4.678728	3.589124	3.758636	1.543645	1.871487	2.152351
	5	3.467792	2.5644	2.702225	1.074335	1.303194	1.505006
	7	2.825999	2.177787	2.281103	1.097592	1.273137	1.41086
MRSS	3	2.893722	1.992761	2.128798	0.511588	0.71559	0.909876
	5	1.84941	1.370974	1.443581	0.573632	0.694933	0.804199
	7	1.328728	1.003913	1.049678	0.506203	0.5859	0.653944
PRSS	3	1.459251	1.072819	1.118774	0.426448	0.526275	0.607975
	5	0.938814	0.711453	0.743337	0.322499	0.38239	0.435426
	7	0.808612	0.63207	0.659108	0.315371	0.365548	0.409602
DMRSS	3	1.947372	1.326942	1.426087	0.344733	0.481088	0.611981
	5	0.979659	0.735432	0.780801	0.305779	0.370446	0.428304
	7	0.578333	0.449038	0.467461	0.230676	0.266573	0.297756
MDRSS	3	2.254737	1.568706	1.675866	0.401672	0.560457	0.71322
	5	1.293731	0.950794	1.003327	0.396653	0.480465	0.555669
	7	0.804725	0.626488	0.652385	0.322667	0.370226	0.412472

k consecutive observations, which satisfies a certain out-of-control criterion (with the condition that $0 < m \leq k-1$; details may be found in Riaz et al. 2011). The specific choices of the dispersion estimators include the sample statistics, which are based on the standard deviation (S), the range (R), Gini's mean differences ($GINI$), the mean of the median of the average absolute deviations (MAD), and a robust estimator of the standard deviation (Q_n). Details of these estimators may be found in Schoonhoven et al. (2011) and Abbasi and Miller (2012). Next, we provide only the final outcomes of our investigations. For the above-mentioned structures of the dispersion charts we derived the design parameter quantities through Monte Carlo simulations. We simulated the constants to be used to obtain unbiased estimates for the standard deviation σ and the coefficients to be used for deriving the limits of the control charts for dispersion for $n=3$, 5, and 7 and false alarm rate $\alpha=0.0027$. The resulting outcomes are given in Tables 1 and 2. The specific choices of sampling strategies are SRS (benchmark), MRSS, PRSS, DMRSS, and MDRSS. This was based on Mehmood et al. (2013).

Using these quantities we carried out a detailed simulation study to evaluate the performance (in terms of the power) of these ranked set strategies–based dispersion charting structures with runs rules schemes. The resulting power measures are displayed in the form of power curves for varying choices of sample sizes (n), runs rules (($k-m$) out of k), sampling strategies (denoted by T), and dispersion estimators (S, R, $GINI$, MAD, and Q_n) for different amounts of shifts (δ) in the process dispersion. Some useful curves are produced in Figure 6.

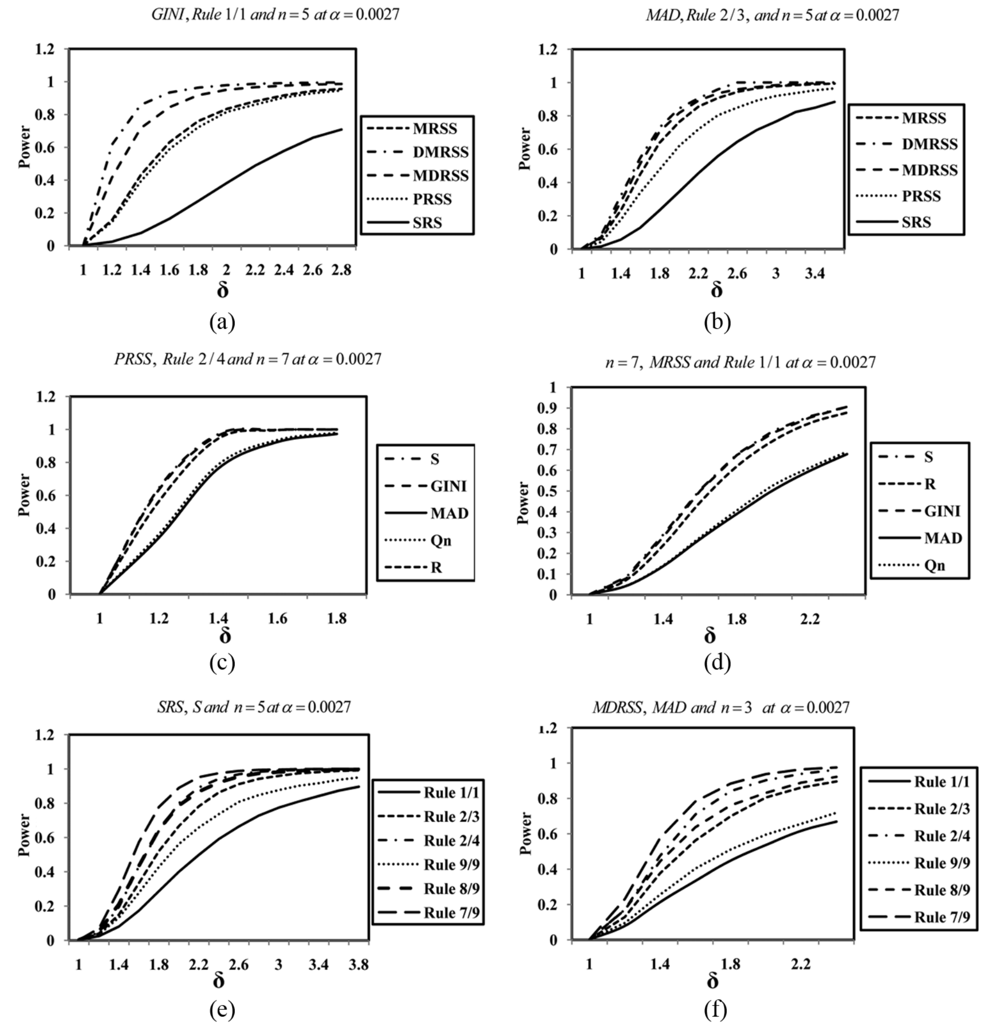

FIGURE 6 **Some power curves of different rank set–based control charts for dispersion.**

The power analysis reveals that the ranked set sampling design structures of the proposed charts are more accommodative and keep improving their performance with the increase in different quantities including n, k, $k - m$, and δ. The proposals outperform the SRS-based design structure, the usual S charts, and the runs rules–based design structures of the S charts given by Riaz et al. (2011). With respect to the sampling methodologies, double-ranked set strategies perform better than the single-ranked set strategies in general. In the class of single-ranked set strategies the superiority order is MRSS, PRSS, SRS, and in the double-ranked set group the dominance order is DMRSS, MDRSS with varying runs rules schemes and a variety of dispersion estimators (cf. Figure 6).

The performance order of the different dispersion estimators–based control charts under varying runs rules schemes is as follows: for small sample sizes the S_T, $GINI_T$, and R_T charts are close competitors, and MAD_T and Q_{n_T} charts perform relatively poorly; for moderate and large sample sizes the design structures of S_T and $GINI_T$ charts exhibit the best performance, and R_T, MAD_T, and Q_{n_T} present relatively low detection abilities for the process environments under consideration in this study. It should be mentioned that the special cases of the proposals include the usual SRS (e.g., the usual Shewhart-type control charts based on *S, R, GINI, MAD*, and Q_n charts. cf. Abbasi and Miller 2012; Schoonhoven et al. 2011) and the runs rules–based design structure of R and S charts (cf. Riaz et al. 2011).

A Real-Life Example

In this section we provide an application of the ranked set strategies–based dispersion charts with

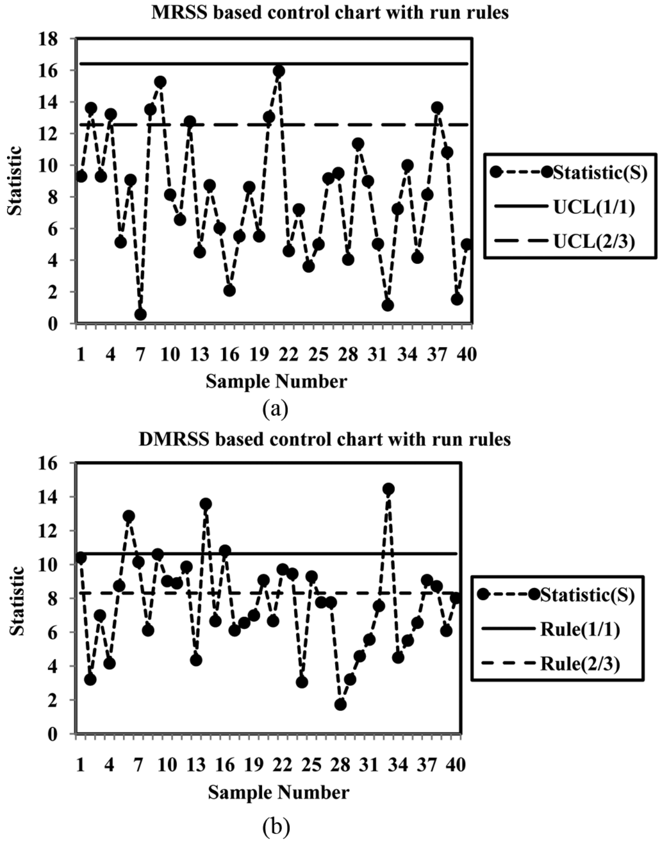

FIGURE 7 Two control charts for dispersion of the real-life data set.

runs rules to monitor the process of filling water. We used data sets (samples on 40 time points, each of size 3) collected from a real production line using MRSS and DMRSS. The data are collected with the collaboration of Sky Water Company situated in Rahim Yar Khan, Pakistan. The company is interested in running the process with mean $\mu = 1{,}500$ mL and standard deviation $\sigma = 10$ mL. We have constructed some useful dispersion charts under discussion. We present here two selective runs rules (i.e., one out one; e.g., a signal appears when the process statistic is outside the control limits) and two out of three (e.g., a signal appears when two out of three consecutive observations are outside the 2-sigma limits) for the S chart based on MRSS and DMRSS (cf. Figure 7).

From Figure 7 it is clear that DMRSS performs better than MRSS. Moreover, by implementing efficient runs rules we may be better able to detect small shifts in the process. These results show the importance of the proposed ranked set and runs rules–based dispersion charting structures in industry.

SUMMARY AND CONCLUSIONS

In this column we discussed the details of different ranked set strategies for practitioners' interests and explained their applications in an industrial process using control charts. On the process monitoring side, we showed the application of different sampling strategies by implementing the runs rules schemes with some selective dispersion control charts. We observed that ranked set sampling schemes are quite useful in practice for monitoring process parameters. The double-ranked set schemes offer better detection abilities relative to the single ones in general.

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