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Objective Metric Study for DOE-Based Parameter Optimization in Robotic Torque Converter Assembly

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Abstract - **This paper presents the objective metric study on Design Of Experiments (DOE)-based robotic force control parameter optimization in transmission torque converter assembly. Based on a real-world assembly production process, investigation and analysis are performed on the optimization metrics of assembly cycle time mean (MEAN), its mean plus three times of standard deviation (MEAN+3*STDEV), and First Time Through (FTT) rate. Simulations have been conducted to illustrate and explain the findings in the parameter optimization practice. Practical metric criteria have been proposed and discussed. An on-pendant robotic assembly parameter optimization tool with the objective metric concept is introduced. And automatic parameter optimization or on-line robot learning feature is also mentioned in terms of the objective metrics for the particular robot assembly parameter optimization tasks. Finally conclusions are drawn and discussion and further investigation is proposed.**

Index Terms – Industrial robot, force control, Design of Experiments, parameter optimization.

I. INTRODUCTION AND BACKGROUND

Robot force control has been increasingly used in assembly and machining processes in both automotive and general industries. This recent advance in industrial robot control gives a "touch" sensing to industrial robots and permits an entire new class of robot behaviors and applications. The new robot behaviors are possible due to the incorporation of force sensor, sometimes combined with vision, into the robot control system. Industrial robot applications have been now expanded into processes with contact forces such as tight-fitting assembly and machining since the contact force with the environment can be controlled. The force control robot technology enables robotic automation applications that mate parts together such as gear meshing, spline insertion, clutch hub assembly, surface grinding following complex curved geometry and so on. Cited papers [1], [2], and [3] dealt with force control technology and applications in more detail.

On the other hand, robot force control introduced complexity and uncertainty to the robot programming, control parameter setting up, and manufacturing process cycle time. The force-controlled robot behaves differently for different contact force conditions resulting from the manufacturing variations of the assembled parts, fixture and environment disturbances on the manufacturing floor. One of the most recognizable behavior differences from position-controlled robot is that the robot motion cycle time is no longer a predetermined value in force control. Normally, it will be distributed in a statistical manner for robotic assembly processes. And the mean and standard deviation of the assembly cycle time and FTT rate become the measurement and the optimization objectives of a force-controlled robot assembly system. Since the statistical nature of the assembly task and DOE's increasing popularity in manufacturing quality control, DOE has been used in the robot assembly parameter optimization. The cited paper [3] gives overview on use of DOE method in torque converter assembly parameter optimization. MEAN+3*STDEV was proposed to be used as an objective metric for a group of 10 replicates/trials for each DOE design. Cited paper [4] introduces an on-pendent robotic assembly parameter optimization tool based on DOE with optimization metrics of cycle time MEAN, MEAN+3*STDEV and First Time Through success rate (FTT). This section will briefly describe the basics of robot force control, robotic torque assembly and parameter optimization. Section II of this paper will focus on objective metric study for DOE-based robotic force control parameter optimization in transmission torque converter assembly. Based on a real-world assembly production process, investigation and analysis have been performed on the optimization metrics of MEAN, MEAN+3*STDEV, and FTT rate. MATLAB simulations have been conducted to illustrate and explain the findings in the parameter optimization practice. Conclusions will be drawn and analyzed and further investigation is proposed and discussed in Section III.

A. Robot Force Control and Torque Converter Assembly

Force control has been a feature on ABB Robotics' standard products. The feature was included in two separate options: *Force Control Assembly* and *Force Control Machining*. The hardware is identical and tightly integrated into ABB IRC5 controller, which includes a force sensor, axis computer board and cables. 6-D force signals (3 forces and 3 moments) from the force sensor through a PCM A/D card as shown in Figure 1. Figure 2 gives a simplified control diagram of the robot force control. The difference between commanded and measured force values, divided by the Damping Factor (DF) and smoothed by a Low Pass Filter (LPF), is used as additional feedback in the velocity control loop. Active search pattern can be designed and input to the control system through $V_{reference}$ (velocity reference). DF and LPF can be tuned for specific robotic system and different assembly applications. Through velocity reference input, active search can be performed through different patterns or combinations of the patterns such as linear, circular, spiral, and rotational. Same as position control, the force control features can be programmed by using standard ABB robot programming language, RAPID. Reference the cited [8] - *Robotics Application Manual – Force Control for Assembly* for detail.

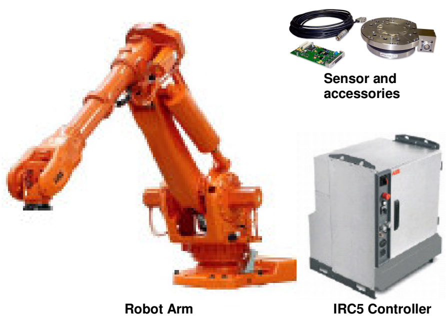

Fig. 1. The force control hardware components

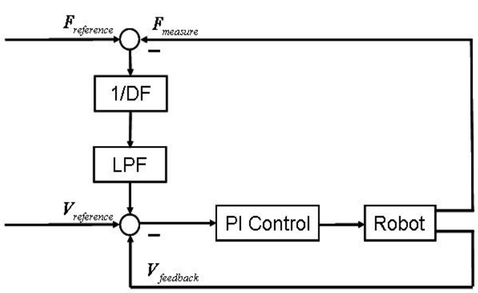

Fig. 2. The simplified force control diagram

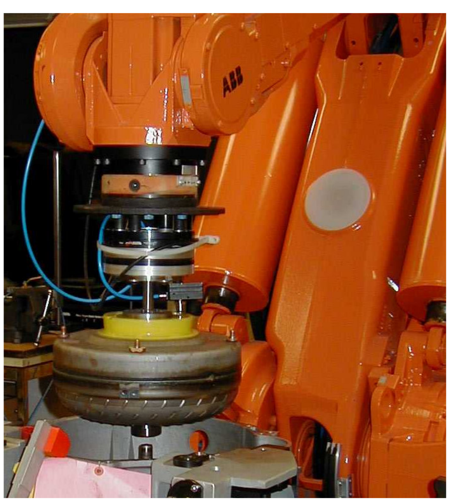

Fig. 3. The first robotic torque converter assembly prototype

A joint effort between Ford AMTD and ABB Corporate Research Center (CRC) was made to target the complicated robotic torque converter assembly issues several years ago. The first force control torque converter assembly prototype was built and demoed in CRC Lab. Figure 3 shows the first robotic torque converter assembly unit developed at CRC in 2003. Thereafter, with close collaboration among Ford and ABB Robotics and Corporate Research Center, the robotic torque assembly cells have been successfully installed in multiple production lines with different types and models at Ford and Chrysler. The force control feature has been symmetrically integrated into ABB's latest robot controller IRC5.

B. *Assembly Parameter Optimization*

The robotic torque converter assembly cell operates in a continuously-running production line. Similar to other automatic production lines, a certain throughput is designed and maintained in order to have smooth production. So the robotic torque converter assembly process not only has to perform the assembly successfully, but also has to finish the assembly within certain amount of time which depends on the production throughput and the line buffer size. Since the assembly time is statistically distributed, mean plus three times of standard deviation is a proper measurement to meet the throughput for most of the assembly cases. A DOE is used in robotic torque converter assembly parameter optimization. There are dozens of parameters involved in the force control based assembly process and 7 to 10 of them are often varied to achieve optimal goals or objective metrics. The typical DOE-based parameter optimization steps normally are 1) using various types of fractional factorial experiments to identify the most influential parameters; 2) using full factorial experiments to find the optimal parameter set; and 3) verifying the optimized parameter set through running a number of experiments and checking on the distribution of the objective metrics. The optimized parameter number and the number (level) of values for each parameter can be varied widely based on the sensitivity of the optimization goals to the parameter change, the available number of tested parts and the cost of the experiment.

At early stage of the optimization work, the experiments were designed off-line by use of MINITAB on a PC and programmed into robot motion program such as RAPID. The robot program runs on the actual or close to actual production environment and the result data is collected. The data file is then taken off from the robot controller and imported into MINITAB for analysis. Cited paper [3] describes the optimization process in more detail. This process is often needed to be done for several iterations. There are several professionals needed to be collaborated in performing this optimization task, including a manufacturing quality control expert to analyze the assembly process and design proper DOE experiment, a robot programming to code the designed into robot program, an operator to execute the program, and then the quality control person takes over the data and analyzes it and designs a new experiment – the optimization cycle is started again. To simplify the optimization process, improve the efficiency and make the optimization process down to the manufacturing floor, an on-pendant robotic assembly optimization tool has been developed.

Cited paper [4] presents a prototype of the on-pendant assembly optimization software package. In this software package, the robotic assembly process (using torque converter assembly as a development platform but the tool can be used for various assembly processes of other types) has been firstly parameterized into operator-understandable terms and parameters such as starting point, assembly stage, insertion distance, timeout limit, max number of trials, searching force, rotation speed, rotation angle, force amplitude, force (sine wave) period and so on. A robot program module is written to convert the process related parameters into robot force control parameters and corresponding robot motions to perform a particular assembly task. Then, a DOE design and analysis function have been simplified specifically for the robotic assembly applications and coded into a C# library to realize the DOE design and analysis on the touch-screen robot teach pendant - FlexPendant. Finally, a graphical user interface (GUI) was developed using early version of ScreenMaker teach pendant GUI design and programming software. The GUI provides interface to setup, execute and analyze the parameter optimization process at a single point on the robot teach pendant. With some basic training, a robot operator could be able to perform the optimization without a quality control expert and expensive commercial statistics analysis software such as MINITAB and the optimization time could be significantly reduced. Figure 4 shows the on-pendant assembly optimization development lab test setup with a FlexPendant on the lower-left corner; Figure 5 gives the main page of the latest development of the on-pendant optimization tool; Figure 6 shows a typical Pareto plot from a screening process; Figure 7 is a typical result from a 3-parameter with 3-level optimization. The three parameters are Circular Speed, Search Force Amplitude and Period in Z direction; and Figure 8 shows a typical assembly cycle time distribution plot.

Fig. 4. The parameter optimization tool development lab setup

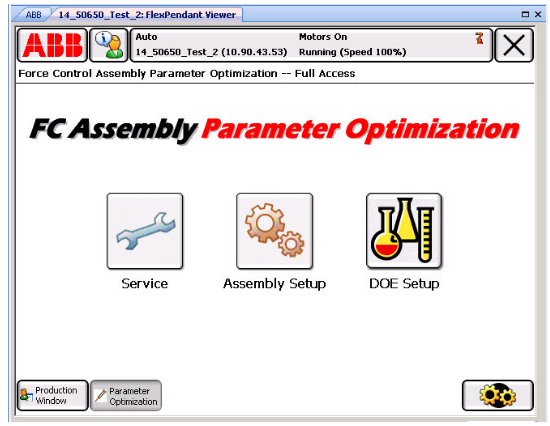

Fig. 5. Main page of the latest GUI

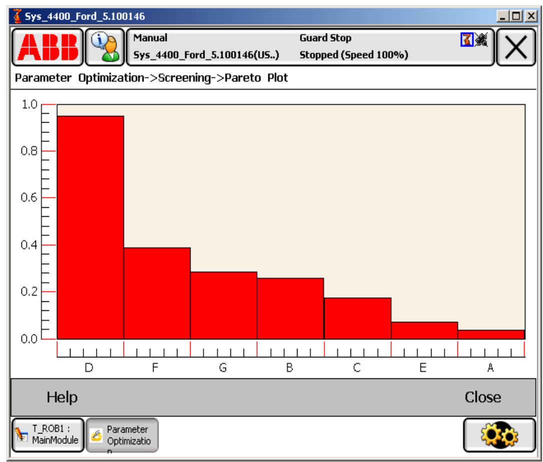

Fig. 6. A typical Pareto plot from screening process

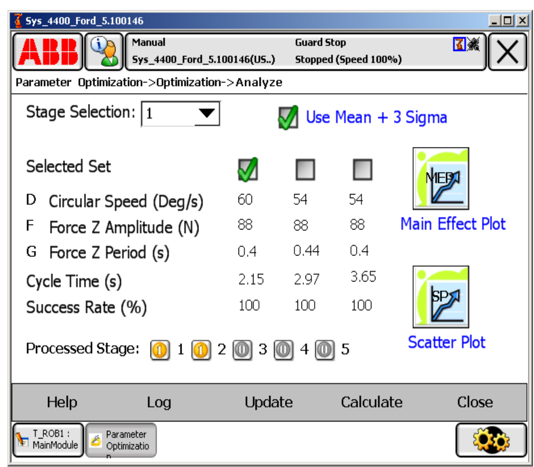

Fig. 7. A typical optimization result page

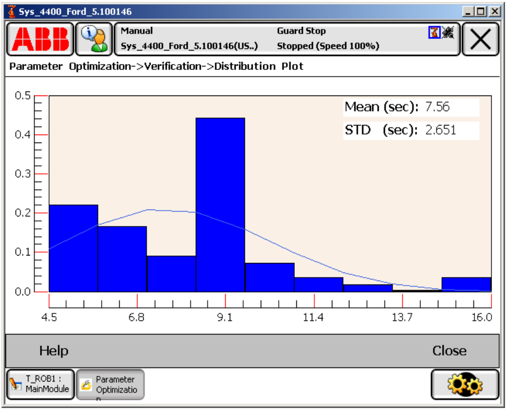

Fig. 8. A typical assembly time distribution plot

No matter if using an off-line designed DOE method or using the on-pendant assembly optimization tool, an understanding of the fundamentals of the DOE-based optimization, the characteristics of the assembly process, and the robot force control functionality is the core knowledge or expertise needed in effectively conducting the robotic assembly and pushing the automation system toward its optimal performance. Authors of this paper have gone through the torque converter robotic assembly optimization process along with many other robotic assembly applications. From the experience, we gain some understanding or knowledge on the objective metrics that could be used and the ways they may be used in the optimization process. The following section gives a detail description on this topic. MATLAB simulation is used to illustrate and help in explaining the intuitive concepts in a statistical manner.

II. Objective Metrics for Robotic Torque Converter Assembly

Running DOE in the midst of production often requires truncating the cycle time to a reasonable limit so that the station does not become a bottleneck for the continuously-running production line during the parameter optimization process. If the MEAN+3*STDEV of assembly cycle time is lower than the cycle time limit, almost none of the population will be artificially truncated by the cycle time limit. However as the MEAN increases, or as the MEAN+3*STDEV becomes larger than the cycle time limit, more of the population will be truncated by the limit and the histogram of the distribution will tend to pile up at the cycle time limit value. This phenomena can be illustrated in Figure 9.

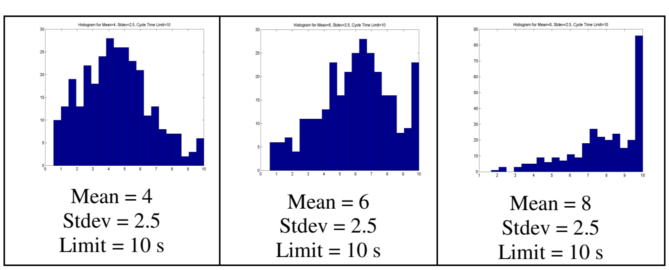

Fig. 9. The histograms of a population at various input means of 4, 6, and 8 sec.

As the population of MEAN shifts right towards the cycle time limit (10 seconds), an increasing fraction of the population will be timeout at the cycle time limit. These units represent a loss to FTT for the production station. Using a mathematical model (Normal distributed with a varying MEAN and fixed STDEV) with an input population standard deviation of 2.5, it can be seen on Figure 9, if the cycle time limit is 10 seconds, when the MEAN equals the cycle time limit of 10s, 50% of the population will be over 10 seconds. When the population MEAN-(3*STDEV) approaches the cycle time limit plus its 3*STDEV, nearly 100% of the population will experience a station timeout as we would expect.

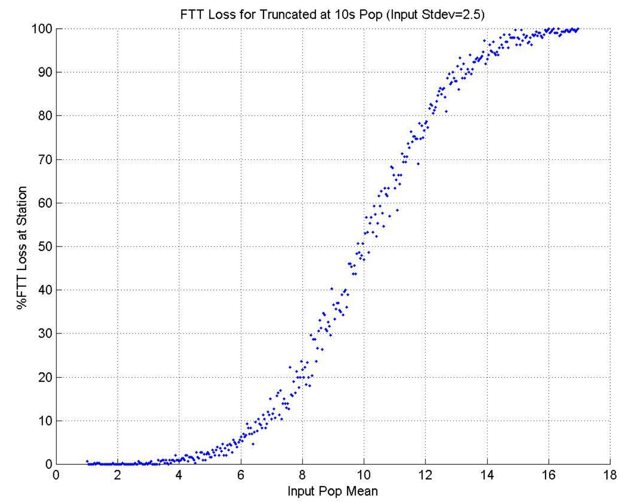

Fig. 10. The effect on FTT as the population input MEAN increases. The cycle time limit here is 10s.

In previous torque converter assembly DOE work [4], we successfully applied the optimization metric of the MEAN+3*STDEV which is an estimate of maximum the cycle time at relatively high FTT rate > 90%. However, when there is a significant FTT loss due to hitting the cycle time limit, the MEAN and STDEV signals become corrupted by the truncated distribution, making this optimization metric less meaningful. We postulate that if there is significant degradation of the MEAN and STDEV signals for populations due to station timeouts, it will be advantageous to use a pass/fail metric in lieu of MEAN+(3*STDEV) metric. Using a MATLAB mathematical model with a fixed standard deviation of STDEV=2.5, and 300 samples (N=300), and varying the population input MEAN values from 0 to 17 seconds, we can calculate the effects of MEAN, STDEV and MEAN+3*STDEV and on the DOE optimization metrics. The following subsections analyze and discuss the truncated distribution effect on different objective metrics.

A. Truncated Distribution Effect on the MEAN

Fig. 11 shows the MEANs for the normal sample population and the truncated sample population diverge as the MEAN value approaches the cycle time limit. The MEAN values for the normal and truncated populations remain to be similar until the MEAN value reaches approximately the cycle time limit minus one (1) STDEV. After that, the MEAN value loses its effectiveness as an optimization metric. See Figure 11 below for reference.

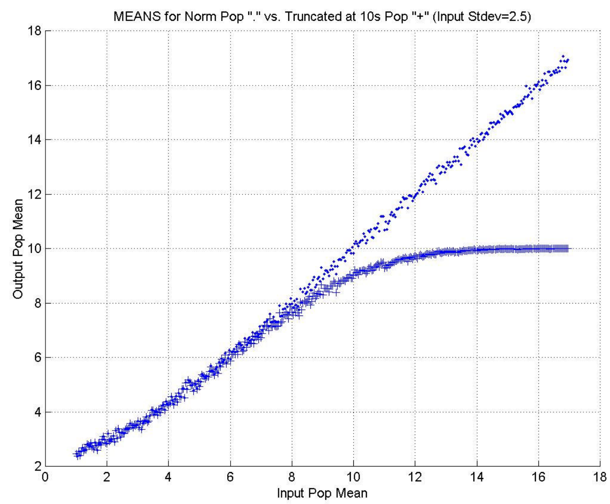

Fig. 11. Effect on the MEAN values for a normal population and a population truncated at 10s.

B. Truncated Distribution Effect on the STDEV

From Figure 12, we see that the STDEV for the normal and truncated populations are similar at beginning and start diverging when the MEAN approaches the cycle time limit. At the cycle time limit, since no cycle times over the limit are possible, half of the population will be truncated and the STDEV is much smaller than the one from normal population. The STDEV is misleading to be used as an optimization metric.

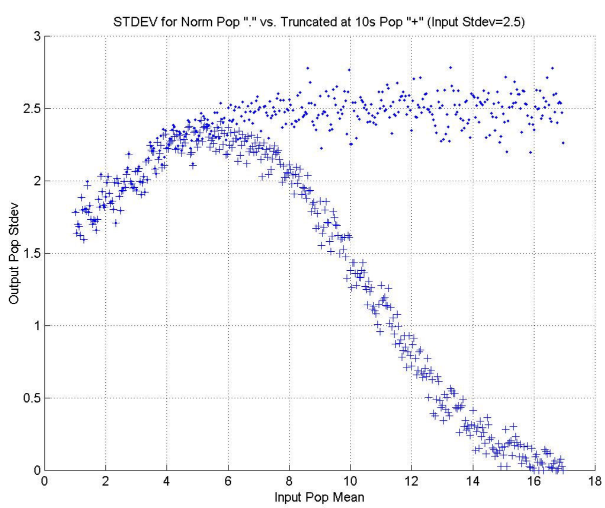

Fig. 12. Effect on the STDEV values for a normal population and a population truncated at 10s.

*C. Truncated Distribution Effect on the MEAN+3*STDEV*

The MEAN+3*STDEV was successfully used in earlier work as the optimization metric for DOE's that tuned the robot parameters for optimal performance at high FTT rate. However, from Figure 13, you can see that the normal population and the truncated populations diverge too as the MEAN approaches the cycle time limit, and the MEAN+3*STDEV also becomes ineffective to be used as an optimization metric. This scenario is understandable since MEAN+3*STDEV is the combination of the MEAN and STDEV.

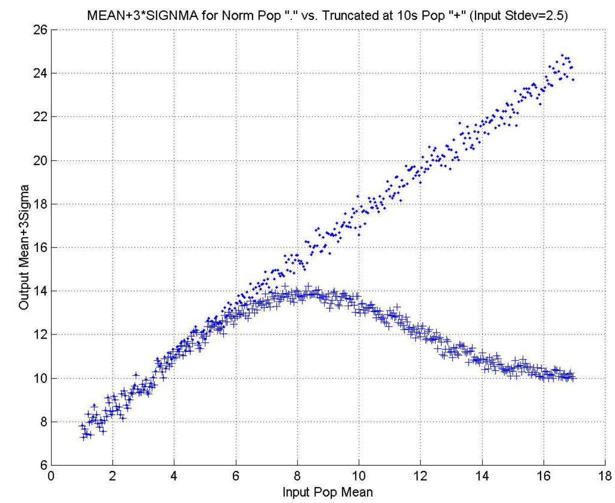

Fig. 13. Effect on the MEAN+3*STDEV values for a normal population and a population truncated at 10s.

D. Effect of Number of Replicates to the Objective Metrics

When STDEV is used with MEAN as the objective metric, same experiment needs to be executed repeatedly to get a reasonable STDEV. The reliability of the STDEV value depends on the level of stability of the manufacturing system and the number of the replicates. For robotic torque converter assembly, Ten (10) is the number that we believed to be a proper considering the experiment cost and optimization result benefit. Some times, less repeated tests have to be taken because of the availability of the test parts and execution time constrain. With the decreasing of the number of replicates, the quality of the STDEV declines. Experience tells that five (5) is the minimum number that calculated STDEV value can be reasonably used as part of the objective metrics.

E. Recovery from the Truncated Experimental Data

When the FTT rate is not too low (between 75% and 90 %), theoretically, the truncated experimental data could be recovered for being used in DOE analysis. Let's use a data set with MEAN = 8 sec, a STDEV = 2.5, cycle time limit is 10, and FTT rate is 78.2% as an example to illustrate the recovery process. From MATLAB simulation, we can know that the "actual" MEAN calculated from the truncated data set will be 7.7 and the STDEV calculated will be 2.04. The steps to recover the data could be that, firstly, to recover the mean from the truncated data. With the assumption of that the experimental data is Gaussian distributed, the recovery steps are 1) remove the data values which are less than cumulative probability distribution which is 100% - 78.8%=21.2%; 2) remove the data values which are greater than 78.8% from the frequency number in the last internal of the distribution plot; 3) average the data values after the removal to get the new MEAN; then 4) remove the data values which are greater than the new MEAN from the original data set and 5) calculate the new STDEV

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2},$$

using of "half" of the data set in the un-truncated side (left side). In the example, the recovered MEAN from the truncated data is 8.0052 and recovered STEDV is 2.472. They are very close to the values used in the simulation. Figure 14 gives the simulation plot for the data recovery process.

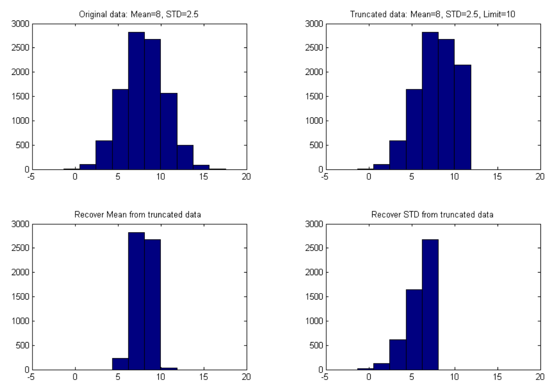

Fig. 14. Truncated data recovery simulation plots: a) Distribution plot from nu-truncated simulation data; b) Distribution plot from truncated simulation data; c) the data plot after removal of the data values smaller and greater than the critical cumulative probability distribution; and 4) the distribution plot of the recovered data (left half).

Then the recovered MEAN and STDEV can be used in the DOE analysis. Notice that there may be a lot more than ten (10) replicates needed in this recovery process. The more of the replicates are, the more reliable the recovered data is.

III. Discussion and Conclusion

This paper introduces force control-based robotic torque converter assembly and parameter optimizations. Collaborative effort between Ford and ABB in DOE-based assembly parameter optimization is presented and discussed. The objective metrics used in the parameter optimization are studied and some new objective metrics that could be used in different scenarios have been proposed, analyzed and discussed based on real-world manufacturing experience. From the investigation, the following data processing guidelines can be concluded:

1) MEAN+3*STDEV can be used as an objective metric in robotic torque converter assembly parameter optimization when its FTT rate is above 90% and the number of replicates is greater than five (5);
2) FTT rate can be used as a optimization metric when it is lower then 90% where MEAN+3*STDEV is altered by truncated distributions;
3) MEAN is a better metric to be used in the DOE-based optimization if the number of the replicates is less than five (5) and FTT rate is greater than 90%;
4) Recovery of the truncated data set is possible if the FTT rate is greater than 75%. And the recovered data set can be used in the optimization but larger number of replicates is needed to make the recovery possible and meaningful.

Further investigations in this area are identified as 1) Use of real-world manufacturing data to further verify the objective mastics and the proposed data recovery method; 2) Applying the objective metrics to the on-line parameter optimization or robot learning. The on-line automatic optimization or learning is demanded and useful when more and more robotic assembly systems are installed and while the resource of quality control and assembly optimization experts and service budget are limited. Another advantage of on-line automatic optimization is that the parts manufacturing variation can be compensated dynamically and the robotic assembly process can be continuously improved; 3) Discover the strategy to recover the truncated data in real-world assembly production process. From the mathematics point of view the number of replicates may need to be dynamically increased based on the FTT rate in order to accurate recovery on mean and standard deviation of truncated data.

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