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MANUFACTURING

Chapter 17

Collecting and Developing Manufacturing Process Capability Models

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17.1 Why Collect and Develop Process Capability Models?

In the recent past, good design engineers have focused on form, fit, and function of new designs as the criteria for success. As international and industrial competition increases, design criteria will need to include real considerations for manufacturing cost, quality, and cycle time to be most successful. To include these considerations, the designer must first understand the relationships between design features and manufacturing processes. This understanding can be quantified through prediction models that are based on process capability models. This chapter covers the concepts of how cost, quality, and cycle time criteria can be designed into new products with significant results!

In answer to the need for improved product quality, the concepts of Six Sigma and quality improvement programs emerged. The programs' initial efforts focused on improving manufacturing processes and using SPC (Statistical Process Control) techniques to improve the overall quality in our factories. We quickly realized that we would not achieve Six Sigma quality levels by only improving our manufacturing processes. Not only did we need to improve our manufacturing process, but we also needed to improve the quality of our new designs. The next generation of Six Sigma deployment involved using process capability data collected on the factory floor to influence new product designs prior to releasing them for production.

Next, quality prediction tools based on process capability data were introduced. These prediction tools allowed engineers and support organizations to compare new designs against historical process capability data to predict where problems might occur. By understanding where problems might occur, designs can easily be altered and tolerances reallocated to meet high-quality standards and avoid problem areas before they occur. It is critical that the analysis is completed and acted upon during the *initial design stage* of a new design because new designs are very flexible and adaptable to changes with the least cost impact. The concept and application of using historical quality process capability data to influence a design has made a significant impact on the resulting quality of new parts, assemblies, and systems.

While the concepts and application of Six Sigma techniques have made giant strides in quality, there are still areas of cost and cycle time that Six Sigma techniques do not take into account. In fact, if all designs were designed around only the highest quality processes, many products would be too expensive and too late for companies to be competitive in the international and industrial market place. This leads us to the following question: If we can be very successful at improving the quality of our designs by using historical process capability data, then can we use some of the same concepts using three-dimensional models to predict cost, quality, and cycle time? Yes. By understanding the effect of all three during the initial design cycle, our design engineers and engineering support groups can effectively design products having the best of all three worlds.

17.2 Developing Process Capability Models

By using the same type of techniques for collecting data and developing quality prediction models, we can successfully include manufacturing cost, quality, and cycle time prediction models. This is a significant step-function improvement over focusing only on quality! An interactive software tool set should include predictive models based on process capability history, cost history, cycle time history, expert opinion, and various algorithms. Example technology areas that could be modeled in the interactive prediction software tool include:

- Metal fabrication
- Circuit card assembly
- Circuit card fabrication
- Interconnect technology
- Microwave circuit card assembly
- Antenna / nonmetallic fabrication
- Optical assembly, optics fabrication
- RF/MW module technology
- Systems assembly

We now have a significant opportunity to design parts, assemblies, and systems while understanding the impact of design features on manufacturing cost, quality, and cycle time before the design is completed and sent to the factory floor. Clearly, process capability information is at the heart of the prediction tools and models that allow engineers to design products with accurate information and considerations for manufacturing cost, quality, and cycle time! In the following paragraphs, I will focus only on the quality prediction models and then later integrate the variations for cost and cycle time predictions.

17.3 Quality Prediction Models - Variable versus Attribute Information

Process capability data is generally collected or developed for prediction models using either variable or attribute type information. The process itself and the type of information that can be collected will determine if the information will be in the form of variable, attribute, or some combination of the two. In general, if the process is described using a standard deviation, this is considered variable data. Information that is collected from a percent good versus percent bad is considered attribute information. Some processes can be described through algorithms that include both a standard deviation and a percent good versus percent bad description.

17.3.1 Collecting and Modeling Variable Process Capability Models

The examples and techniques of developing variable models in this chapter are based on the premise of determining an average short-term standard deviation for processes to predict long-term results. Average short-term standard deviation is used because it better represents what the process is really capable of, without external influences placed upon it.

One example of a process where process capability data was collected from variable information is that of side milling on a numerically controlled machining center. Data was collected on a single dimension over several parts that were produced using the process of side milling on a numerically controlled machine. The variation from the nominal dimension was collected and the standard deviation was calculated. This is one of several methods that can be used to determine the capability of a variable process. The *capability* of the process is described mathematically with the standard deviation. Therefore, I recommend using SPC data to derive the standard deviation and develop process capability models.

Standard formulas based on Six Sigma techniques are used to compare the standard deviation to the tolerance requirements of the design. Various equations are used to calculate the defects per unit (dpu), standard normal transformation (Z), defects per opportunity (dpo), defects per million opportunities (dpmo), and first time yield (fty). The standard formulas are as follows (Reference 3):

dpu = dpo * number of opportunities for defects per unit
dpu = total opportunities * dpmo / 1000000
fty = e^{-dpu}
Z = ((upper tolerance + lower tolerance)/2) / standard deviation of process
sigma = (SQRT(LN(1/dpo)^2)))-(2.515517 + 0.802853 * (SQRT(LN(1/dpo)^2))) + 0.010328 * (SQRT(LN(1/dpo)^2)))^2)/(1 + 1.432788 * (SQRT(LN(1/ (dpo)^2))) + 0.189269 * (SQRT(LN(1 / (dpo)^2)))^2 + 0.001308 * (SQRT(LN(1 / dpo)^2)))^3) +1.5
dpo = [(((((((1 + 0.049867347 * (z –1.5)) + 0.0211410061 * (z –1.5) ^2) + 0.0032776263 *(z -1.5)^3) + 0.0000380036 * (z –1.5)^4) + 0.0000488906 * (z –1.5)^5) + 0.000005383 * (z –1.5)^6)^ – 16)/2]
dpmo = dpo * 1000000

where

dpmo = defects per million opportunities
dpo = defects per opportunity
dpu = defects per unit
fty = first time yield percent (this only includes perfect units and does not include any scrap or rework conditions)

Let's look at an example. You have a tolerance requirement of ±.005 in 50 places for a given unit and you would like to predict the part or assembly's sigma level (Z value) and expected first time yield. (See Chapters 10 and 11 for more discussion on Z values.) You would first need to know the short-term standard deviation of the process that was used to manufacture the ±.005 feature tolerance. For this example, we will use .001305 as the standard deviation of the process. The following steps would be used for the calculation:

1. Divide the ±tolerance of .005 by the standard deviation of the process of .001305. This results in a predicted sigma of 3.83.
2. Convert the sigma of 3.83 to defects per opportunity (dpo) using the dpo formula. This formula predicts a dpo of .00995.
3. Multiply the dpo of .00995 times the opportunity count of 50, which was the number of places that the unit repeated the ±.005 tolerance. This results in a defect per unit (dpu) of .4975.
4. Use the (e^{-dpu}) first time yield formula to calculate the predicted yield based on the dpu. The result is 60.8% predicted first time yield.
5. The answer to the initial question is that the process is a 3.83 sigma process, and the part or assembly has a predicted first time yield of 60.8% based on a 3.83 sigma process being repeated 50 times on a given unit.

Typically a manufactured part or assembly will include several different processes. Each process will have a different process capability and different number of times that the processes will be applied. To calculate the overall predicted sigma and yield of a manufactured part or assembly, the following steps are required:

1. Calculate the overall dpu and opportunity count of each separate process as shown in the previous example.
2. Add all of the total dpu numbers of each process together to give you a cumulative dpu number.
3. Add the opportunity counts of each process together to give you a cumulative opportunity count number.
4. To calculate the cumulative first time yield of the part or assembly use the (e^{-dpu}) first time yield formula and the cumulative dpu number in the formula.
5. To calculate the sigma rollup of the part or assembly divide the cumulative dpu by the cumulative opportunity count to give you an overall (dpo) defect per opportunity. Now use the sigma formula to convert the overall dpo to the sigma rollup value.

When using an SPC data collection system to develop process capability models, you must have a very clear understanding of the process and how to set up the system for optimum results. For best results, I recommend the following:

- Select features and design tolerances to measure that are close to what the process experts consider to be just within the capability of the process.
- Calculate the standard deviations from the actual target value instead of the nominal dimension if they are different from each other.
- If possible, use data collected over a long period of time, but extract the short-term data in groups and average it to determine the standard deviation of a process.
- Use several different features on various types of processes to develop a composite view of a short-term standard deviation of a specific process.

Selecting features and design tolerances that are very close to the actual tolerance capability of the process is very important. If the design tolerances are very easily attained, the process will generally be allowed to vary far beyond its natural variation and the data will not give a true picture of the processes capability. For example, you may wish to determine the ability of a car to stay within a certain road width. See Fig. 17-1. To do this, you would measure how far a car varies from a target and record points along the road. Over a distance of 100 miles, you would collect all the points and calculate the standard deviation from the center of the road. The standard deviation would then be in with the previous formulas to predict how well the car might stay within a certain width tolerance of a given road. If the driver was instructed to do his or her best to keep the car in the center of a very narrow road, the variance would probably be kept at a minimum and the standard deviation would be kept to a minimum. However, if the road were three lanes wide, and the driver was allowed to drive in any of the three lanes during the 100-mile trip, the variation and standard deviation would be significantly larger than the same car and driver with the previous instructions.

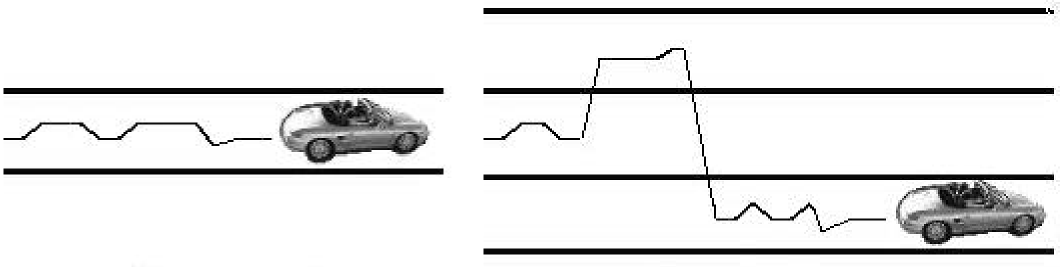

Figure 17-1 Narrow road versus three-lane road

This same type of activity happens with other processes when the specifications are very wide compared to the process capability. One way to overcome this problem is to collect data from processes that have close requirements compared to the processes' actual capability.

Standard deviations should be calculated from the actual target value instead of the nominal dimension if they are different from each other. This is very important because it improves the quality of your answer. Some processes are targeted at something other than the nominal for very good reasons. The actual process capability is the variation from a targeted position and that is the true process capability. For example, on a numerically controlled machining center side milling process that machines a nominal dimension of .500 with a tolerance of +. 005/–. 000, the target dimension would be .5025 and the nominal dimension would be .500. If the process were centered on the .500 dimension, the process would result in defective features. In addition to one-sided tolerance dimensions, individual preferences play an important role in determining where a target point is determined. See Fig. 17-2 for a graphical example of how data collected from a manufacturing process may have a shifting target.

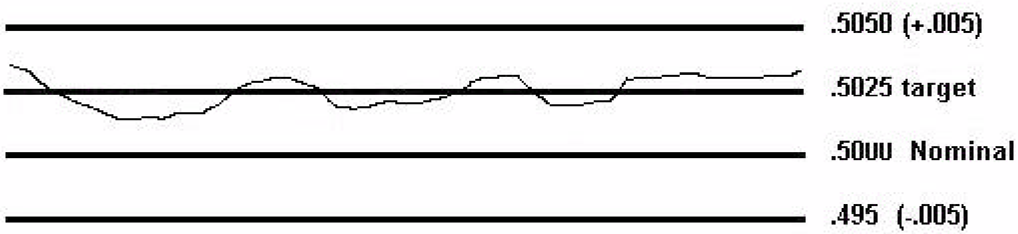

Figure 17-2 Data collected from a process with a shifted target

It is best to collect data from variable information over a long period of time using several different feature types and conditions. Once collected, organize the information into short-term data subgroups within a target value. Now calculate the standard deviation of the different subgroups. Then average the short-term subgroup information after discarding any information that swings abnormally too high or too low compared to the other information collected. See Fig. 17-3 for an example of how you may wish to group the short-term data and calculate the standard deviation from the new targets.

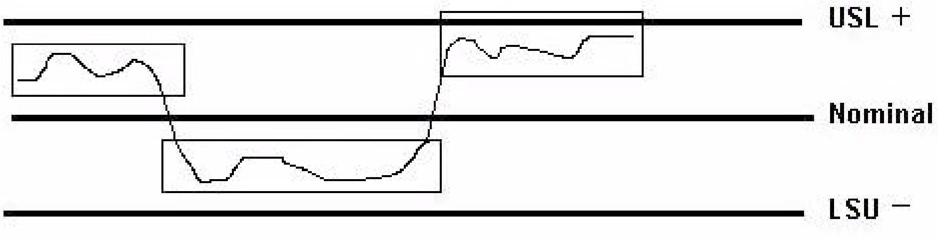

Figure 17-3 Averaging and grouping short-term data

A second method for developing process capability models and determining the standard deviation of a process might include controlled experiments. Controlled experiments are very similar to the SPC data collection process described above. The difference is in the selection of parts to sample and in the collection of data. You may wish to design a specific test part with various features and process requirements. The test parts could be run over various times or machines using the same processes under controlled conditions. Data collected would determine the standard deviation of the processes. Other controlled experiments might include collecting data on a few features of targeted parts over a certain period of time to result in a composite perspective of the given process or processes. Several different types of controlled experiments may be used to determine the process capability of a specific process.

A third method of determining the standard deviation of a given process is based on a process expert's knowledge. This process might be called the "five sigma rule of thumb" estimation technique for determining the process capability. To determine a five sigma tolerance of a specific process, talk to someone who is very knowledgeable about a given process or a process expert to estimate a tolerance that can be achieved 98%-99% of the time on a generally close tolerance dimension using a specific process. That feature should be a normal-type feature under normal conditions for manufacturing and would not include either the best case or worst case scenario for manufacturing. Once determined, divide that number by 5 and consider it the standard deviation. This estimation process gets you very close to the actual standard deviation of the process because a five sigma process when used multiple times on a given part or unit will result in a first time yield of approximately 98% - 99%.

Process experts on the factory floor generally have a very good understanding of process capability from the perspective of yield percents. This is typically a process that has a good yield with some loss, but is performing well enough not to change processes. This tolerance is generally one that requires close attention to the process, but is not so easily obtained that outside influences skew the natural variations and distort the data. Even though this method uses expert opinion to determine the short-term standard deviation and not actual statistical data, it is a quick method for obtaining valuable information when none is available. Historically, this method has been a very accurate and successful tool in estimating information (from process experts) for predicting process capability. In addition to using process experts, tolerances may be obtained from reference books and brochures. These tolerances should result in good quality (98%-100% yield expectations).

Models that are variable-based usually provide the most accurate predictors of quality. There are several different methods of determining the standard deviation of a process. However, the best method is to use all three of these techniques with a regressive method to adjust the models until they accurately predict the process capability. The five sigma rule of thumb will help you closely estimate the correct answer. Use it when other data is not available or as a check-and-balance against SPC data.

17.3.2 Collecting and Modeling Attribute Process Capability Models

Models that are variable models are attribute models. Defect information for attribute models is usually collected as percent good versus bad or yield. An example of an attribute process capability model would be the painting process. An attribute model can be developed for the painting process in several different ways based on the type of information that you have.

- At the simplest level, you could just assign an average defect rate for the process of painting.
- At higher levels of complexity, you could assign different defect rates for the various features of the painting process that affect quality.
- At an even higher level of complexity, you could add interrelationships among different features that affect the painting process.

17.3.3 Feature Factoring Method

The factoring method assigns a given dpmo to a process as a basis. In the model, all other major quality drivers are listed. Each quality driver is assigned a defect factor, which may be multiplied times the dpmo basis to predict a new dpmo if that feature is used on a given design. Factors may have either a positive or negative effect on the dpmo basis of an attribute model. Each quality driver may be either independent or dependent upon other quality drivers. If several features with defect factors are concurrently chosen, they will have a cumulative effect on the dpmo basis for the process. The factoring method gives significant flexibility and allows predictions at the extremes of both ends of the quality spectrum. See Fig. 17-4 for an example of the feature factoring methods flexibility with regards to predictions and dpmo basis.

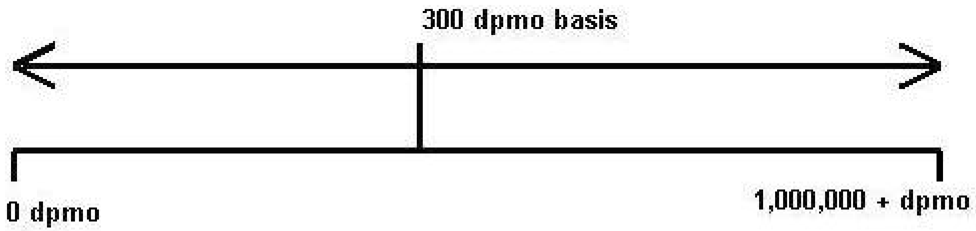

Figure 17-4 Feature factoring methodology flexibility

17.3.4 Defect-Weighting Methodology

This defect-weighting method assigns a best case dpmo and a worst case dpmo for the process similar to a guard-banding technique. Defect driver features are listed and different weights assigned to each. As different features are selected from the model, the defect weighting of each feature or selection reduces the process dpmo accordingly. Generally, when all the best features are selected, the process dpmo remains at its guard-banded best dpmo rating. And when most or all of the worst features with regards to quality are selected, the dpmo rating changes to the worst dpmo rating allowed under the guard-banding scenario.

The following steps describe the defect-weighting model.

1. Using either data collected or expert knowledge, determine the dpmo range of the process you are modeling.
2. Determine the various feature selections that affect the process quality.
3. Assign a number to each of the features that will represent its defect weight with regard to all of the other feature selections. The total of all selectable features must equal 1.0 and the higher the weight number, the higher the effect on the defect rating it will be. The features may be categorized so that you can choose one feature from each category with the totals of each category equal to 1.0.
4. Calculate the new dpmo prediction number by subtracting the highest dpmo number from the lowest dpmo number and multiplying that number times the total weight number. Then add that number to the lowest dpmo number to get the new dpmo number.

The formula is: The new process defect per million opportunity (dpmo) rating
= (highest dpmo number – lowest dpmo number)
× the cumulative weight numbers

For example, you may assign the highest dpmo potential to be 2,000 with the lowest dpmo at 100. If the cumulative weights of the features with defect ratings equal .5, then the new process dpmo rating would be a dpmo of 1,050 (2000 – 100 = 1,900; 1900 × .5 = 950; 950 + 100 = 1,050).

See Fig. 17-5 for a graphic of the defect-weighting methodology with regard to guard-banding and dpmo predictions. This defect-weighting method allows you to set the upper and lower limits of a given process dpmo rating. The method also includes design features that drive the number of defects. The design dpmo rating will vary between the dpmo minimum number and the dpmo maximum number. If the designer chooses features with the higher "weights," the design dpmo approaches the dpmo maximum. If the designer chooses features with lower "weights," the design dpmo approaches the dpmo minimum.

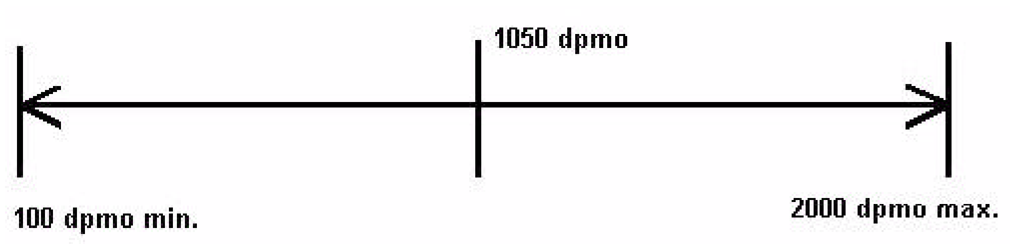

Figure 17-5 Dpmo-weighting and guard-banding technique

17.4 Cost and Cycle Time Prediction Modeling Variations

You might wish to use a combination of both or either of the two previously discussed modeling techniques for your cost and cycle time prediction models. Cost and cycle time may have several different definitions depending upon your needs and familiar terminology. For the purpose of this example, cost is defined as the cost of manufacturing labor and overhead. Cycle time is defined as the total hours required producing a product from order placement to final delivery. Cost and cycle time will generally have a very close relationship.

One method for predicting cost of a given product might be to associate a given time to each process feature of a given design. Multiply the associated process time by the hourly process rate and overhead.

Depending upon the material type and part size, you may wish to also assign a factor to different material types and part envelope sizes from some common material type and material size as a basis. Variations from that basis will either factor the manufacturing time and cost up or down. Additional factors may be applied such as learning curve factors and formulas for lot size considerations. Cost and cycle time models should also include factors related to the quality predictions to account for scrap and rework costs. The cycle time prediction portion of the model would be based upon the manufacturing hours required plus normal queue and wait time between processes. An almost unlimited number of factors can be applied to cost and cycle time prediction models. *Most important is to develop a methodology that gives you a basis from which to start.* Use various factors that will be applied to that basis to model cost and cycle time predictions.

Cost and cycle time predictions can be very valuable tools when making important design decisions. Using an interactive predictive model including relative cost predictions would easily allow real-time what-if scenarios. For example, a design engineer may decide to machine and produce a given part design from material A. Other options could have been material B, C or D, which have similar properties to material A. There may not be any difference in material A, B, C or D as far as fit, form or function of the design is concerned. However, material A could take 50% more process time to complete and thus be 50% more costly to produce.

Here is an example of how cycle time models might be influential. Take two different chemical corrosion resistance processes that yield the same results with similar costs. The difference might only be in the cycle time prediction model that highlights significant cycle time requirements of different processes due to where the corrosion resistance process is performed. Process A might be performed in-house or locally with a short cycle time. Process B might be performed in a different state or country only, which typically requires a significant cycle time. Overall, cost and cycle time prediction models are very powerful complements to quality prediction models. They can be very similar in concept or very different from either the attribute or variable models used in quality predictions.

17.5 Validating and Checking the Results of Your Predictive Models

Making sure your predictive models are accurate is a very important part of the model development process. The validation and checking process of process capability models is a very iterative process and may be done using various techniques. Model predictions should be compared to actual results with modifications made to the predictive model, data collection system, or interpretation of the data as needed. Models should be compared at the individual model level and at the part or assembly rollup level, which may include several processes. Validating the prediction model at the model level involves comparing actual process history to the answer predicted by the interactive model.

With variable models, the model level validation involves comparing both the standard deviation number and the actual part yields through the process versus the first time yield (fty) prediction of the process. The second step of the validation process for variable models requires talking with process experts or individuals that have a very good understanding of the process and its real-world process capabilities. One method of comparing variable prediction models, standard deviations, and expert opinion involves using the five sigma rule of thumb technique.

A 5.0 sigma rating at a specific tolerance will mathematically relate to a first time yield of 98%-99% when several opportunities are applied against it. The process experts selected should be individuals on the factory floor that have hands-on experience with the process rather than statisticians. A process expert can determine a specific standard deviation number. Ask them to estimate the tolerance that the process can produce consistently 98%-99% of the time on a close tolerance dimension. The answer given can be considered the estimated 5.0 sigma process. Using the five sigma rule of thumb technique, divide the tolerance given by the process experts by 5 to determine the standard deviation for the process. You would probably want to take a sampling of process experts to determine the number that you will be dividing by 5. Note that the way you phrase the question to the process experts is very critical. It is very important to ask the process experts the question with regard to the following criteria:

1. The process needs to be under normal process conditions.
2. The estimate is not based on either best or worst case tolerance capabilities.
3. The tolerance that will yield 98%-99% of the product on a consistent basis is based on a generally close tolerance and if the tolerance were any smaller, they would expect inconsistent yields from the process.

After receiving the answer from the process experts, repeat back to them the answer that they gave you and ask them if that is what they understood their answer to be. If they gave you an answer of ±.005, you might ask the following back to them: Under normal conditions, and a close tolerance dimension for that process, you would expect ±.005 to yield approximately 98%-99% product that would not require rework or scrap of the product? Would you expect the same process with ±.004 (four sigma) to yield approximately 75%-80% yields under normal conditions? If they answer "yes" to both of these answers, they probably have a good understanding of your previous questions and have given you a good answer to your question. If you question several process experts and generally receive the same answer, you can consider it a good estimation of a five sigma process under that tolerance.

Compare the estimated standard deviation from that of your SPC data collection system. If there is more than a 20% difference between the two, something is significantly wrong and you must revisit both sources of information to determine the right ones. The two standard deviation numbers should be within 5%-10% of each other for prediction models to be reasonable.

Overall, the best approach to validating variable models is to use a combination of all three techniques to determine the best standard deviation number to use for the process. To do this, compare:

1. The standard deviation derived from the average short-term SPC data.
2. The standard deviation derived from expert opinion and the five sigma rule of thumb method.
3. Using the standard deviations derived from the two methods listed above, enter them one at a time into the interactive prediction tool or equations. Then compare actual process yield results to predict yield predictions based on the two standard deviations and design requirements.

Attribute models are also validated at the model level by comparing actual results to predictive results of the individual model. Similarly, expert opinions are very valuable in validating the models when actual data at the model level cannot be extracted. The validation of attribute models can be achieved by reviewing a series of predictions under different combinations of selections with factory process experts. The process experts should be asked to agree or disagree with different model selection combinations and results. The models should be modified several times until the process experts agree with the model's resulting predictions. Actual historical data should be shared with the process experts during this process to better understand the process and information collected.

In addition to model validation at the individual model level, many processes and combinations of processes need to be validated at the part or assembly rollup level. Validation at the rollup level requires that all processes be rolled up together at either the part or subassembly level and actual results compared to predictions. For a cost rollup validation on a specific part, the cost predictions associated with all processes should be added together and compared to the total cost of the part for validation. For a quality rollup validation on a specific part, all dpu predictions should be added up and converted to yield for comparison to the actual yield of manufacturing that specific part.

17.6 Summary

Both international and industrial competition motivate us to stay on the cutting edge of technology with our designs and manufacturing processes. New technologies and innovative processes like those described in this chapter give design engineers significant competitive advantage and opportunity to design for success. Today's design engineers can work analytical considerations for manufacturing cost, quality, and cycle time into new designs *before* they are completed and sent to the factory floor.

The new techniques and technology described in this chapter have been recently implemented at a few technically aggressive companies in the United States with significant cost-saving results. The impact of this technology includes more than $50 million of documented cost savings during the first year of deployment at just one of the companies using the technology! With this kind of success, we need to continue to focus on adopting and using new technologies such as those described in this chapter.

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