Proceedings of the 8th WSEAS International Conference on APPLIED MATHEMATICS, Tenerife, Spain, December 16-18, 2005 (pp110-117)

Identification of Correlated Characteristics in a Linear Statistical Tolerance Design

JEAN-PHILIPPE CASTONGUAY & ANTOINE S. TAHAN*
Department of Mechanical Engineering
École de Technologie Supérieure
1100 Notre-Dames West, Quebec, H3C 1K3
CANADA
http://www.etsmtl.ca

Abstract: - In order to study the variations of mechanical components of an assembly, the accumulation of tolerances may be calculated using two major approaches: the *Worst Case* method and the *Statistical* (or *probabilistic*) method. The Worst Case method is very simple and well known. It must be applied only for simple assemblies where a larger allowance of the available space is granted for the tolerances. The statistical approach allows us to assign bigger tolerances for each component by taking advantage of random phenomena, which may occur during the manufacturing and assembly. On the other hand, this approach implies several hypotheses which may not always be respected in reality.
This article proposes a case study to model a mechanical assembly of electrochemical cells whereby each cell consists of multiple layers of various materials. The first part of the study describes our main working hypothesis that encompasses the variability of environmental conditions (such as temperature, charge, pressure, shape defects, etc.) that necessitated the introduction of corrective semi-empirical factors. The second part contains the mathematical model, which describes the stochastic behavior of the thickness of cells once they are assembled. This model integrates the variance of each of the materials and the resulting effects of correlation between the materials, as well as the effects of the auto correlation into the case of several layers of the same material.
The study demonstrates that the correlation and the auto correlation combine with different capability indices allows more precise predictions during the modeling stage. This allows the designer to optimize the parameters of the design to maximize the mechanical and energy performances of the electric cells.

Keywords: - Statistic tolerances, Correlation, Robust engineering, Quality, Process controls.

1 Introduction

Going all the way back to it's beginnings in the 1960's [1], the use of the statistical tolerances was already demonstrated in several cases, to represent a very effective and efficient method of estimating the behavior of an assembly of multiple components [2]. This subject has since been in constant development. Presently, a process is underway to standardize the various approaches which will then be integrated into industrial applications globally [3].
An analysis performed using this method allows the prediction of the stochastic behavior of an assembly by including the variations inherent in each component. However, the results obtained are directly dependent on a working hypothesis. Recently, studies [4;5] have demonstrated that in certain cases (presence of correlation, assembly methods, etc.) the 'classic' statistical model becomes deficient. In these cases, it has also been demonstrated that the model must be 'refined' [6] to better express the interactions between the variables which make up the transfer functions.
A statistical study of multiple layers must take into account the effects of correlation and of auto correlation [7-9, 16]. Furthermore, the analysis must take into account each of the distribution methods in order to maintain the performances within target values. Indeed, processes with excellent repeatability capacities, (high value of capability C_p) can present acceptable values for indications of localization C_{pk} (e.g. 1.33-1.67), with an error on the bias exceeding 50% of the required tolerance.
The main economic advantage of using the statistical approach rather than the *Worst Case* approach lies in the fact that they allow a relaxation of tolerances, which generally translates into a decrease in manufacturing costs. As well, the final quality of the product is also improved because this approach ensures a better control of the processes (decrease of the variability and maintenance of the processes on target values). However, a good knowledge of the random characteristics of each of

the variables and their interactions is essential to building a coherent model with a good prediction capacity.

This study aims to contribute to the use of statistical methods in the case of strong correlations. The purpose being to study the behavior of an assembly in the most realistic manner possible. The objective of this analysis will be to maximize the energy capacity stored inside a restricted space by an electrochemical cell. The characteristics of the Lithium Metal Polymer (LMP) battery are described in several publications [10-12]. Concretely, we shall try to estimate the stochastic behavior of each of the components, to obtain their mutual influences (correlation and inter correlation), and finally to integrate them through a general model. The final result will be the global behavior of the assembly (total electrochemical height of cells once assembled), as well as practical recommendations for reducing the variations during the definition of the control parameters of the manufacturing and assembly processes.

The first part of the article defines the general mathematical model used for this study. We introduce coefficients of correction for each variable in order to consider the variations due to various phenomena. Thus, the compensations due to temperature, applied pressure, shape defects and electrical load, are obtained by the introduction of corrective factors. These factors in certain cases, stem from a physical well-known model (temperature and pressure) and, in others, are identified from an experimental semi-empirical model. The second part of the study presents the mathematical development that details the modeling for each of the various levels. The last part describes the experimental methodology used to collect the data that is used to define the various coefficients needed to develop the model.

2 Mathematical Modeling

The goal of this analysis is to model the dimensional variation of the total height (y) of a battery composed of multiple layers. The mathematical modeling will be processed by level, with each level corresponding to a stage of a well-defined assembly. The advantage of working by level is that it allows a better estimation of the results at every stage of the manufacturing process, and the introduction of corrections when necessary. It is important for a model to be most representative of reality in order that the height is maximized without incurring too much risk of interference. Thus, we can maximize the quantity of energy inside the battery without significantly increasing the cost of rejections.

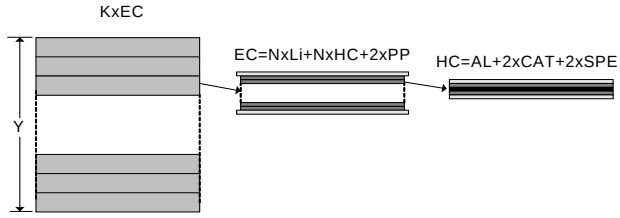

Fig. 1. Simplified representation of the composition of the batteries according to the three levels of the assembly

Each battery consists of (K) electric cells (EC). The total height (y) can be expressed by the following linear equation:

$$y = \sum_{i=1}^{K} x_{ECi} \tag{1.}$$

Each EC consists of laminates of (N) layers of Lithium (Li) and of half-cells (HC). This assembly is protected by two layers of polymer (PP), which is used to insulate electrically every half-cell.

$$x_{EC} = \sum_{i=1}^{N} x_{Li_i} + \sum_{i=1}^{N} x_{HC_i} + x_{PP_i} + x_{PP_2} \tag{2.}$$

Finally, the half-cell (HC) consists of a current collector that acts as a physical support and is comprised of an aluminum sheet (Al), of two cathodic layers (CAT), and two layers of an electrolyte material named (SPE).

$$x_{HC} = x_{Al} + x_{CAT_1} + x_{CAT_2} + x_{SPE_1} + x_{SPE_2} \tag{3.}$$

2.1 Correction factors

Several factors may influence the height of the battery as well as that of the EC's. Environmental conditions are so different between the various stages of the assembly and of the operation that these corrective factors are absolutely necessary. These factors need to be adequately modeled in order to ensure the proper control of all the measurable parameters that may come into play during the manufacturing process, as these are likely to significantly influence the final height. In this article, our model considers a linear-type corrector. However, a more detailed study is currently under development and should ensure the validity of this hypothesis and/or allow the production of a better model. The following equation introduces the variations of the current parameters at the level of assembly of the EC electric cells.

$$x'_{EC_i} = k_1 \times k_2 \times k_3 \times x^*_{EC_i} \tag{4.}$$

$$x_{EC_i} = x'_{EC_i} + k_4 \tag{5.}$$

where,

$x^*_{EC_i}$ Is defined as the thickness of the electric cell at 20ºC, without pressure (Free State), (perfect flatness of the contact areas between layers) and full load.

k_1 Coefficient which corrects shape defects while the constituents are stacked up.

k_2 Coefficient which takes into account the thermal expansion of electrochemical cells.

k_3 Coefficient which corrects the effect of compressibility due to a pressure applied to electrochemical cells.

k_4 Coefficient which takes into account the state of the load inside electrochemical cells engendered by an ionic movement.

Table 1. Coefficients of parameters by elements

	$k_1 = k_{\text{rustle}}$	$k_2 = k_{temp}$	$k_3 = k_{pressure}$	$k_4 = k_{load}$
x_{Al}	f_{AL}	$1+\alpha_{AL}\times\Delta T$	≈ 1.0	1
x_{CAT}	f_{CAT}	$1+\alpha_{CAT}\times\Delta T$	$1-P/E_{CAT}$	1
x_{SPE}	f_{SPE}	$1+\alpha_{SPE}\times\Delta T$	$1-P/E_{SPE}$	1
x_{Li}	f_{Li}	$1+\alpha_{Li}\times\Delta T$	≈ 1.0	$\frac{\Delta G}{SA}\times\Delta Ah$
x_{PP}	f_{PP}	$1+\alpha_{PP}\times\Delta T$	≈ 1.0	1

where α_i represents the thermal coefficient of expansion, ΔT is the difference in temperature with respect to the reference temperature (20ºC), P is the pressure applied (MPa), and E_i is the *Young* modulus (MPa).

Some factors were neglected because they have practically no impact on the global behavior of the variable. Thus, for the load coefficient only the cathode and the lithium are affected by the load state, therefore only the load coefficient of the lithium will be considered. The variable ΔG (m^3/J) corresponds to the variation in volume with regard to the difference in energy. SA (m^2) is the active area in contact with the lithium. ΔAh corresponds to the variation in ampere-hour between both load states. These are presented as variables because they can vary according to various battery designs. For the coefficient $k_{pressure}$, we can ignore the compression of the aluminum because the other materials studied are much softer and thus have a much more significant impact. For the coefficient k_1, the data will be identified experimentally.

2.2 Modeling approach

To be able to properly estimate the behavior of the multi-layer assembly, it is necessary to take into account variations that are inherent in the manufacturing of the constituents. To that end, two approaches are possible: the Worst Case approach and the Statistical approach. As has been demonstrated by numerous studies [3-5, 16], the statistical approach contains major economic advantages because it allows larger tolerances. But the method of statistical calculation implies a special attention to describe the stochastic behavior of the random variables (distribution law, correlation between variables, etc.). The statistical study of a linear assembly of several constituents was generally developed by Cox [13], and specifically for this problem by Tahan [5]. The equations (5) model the behavior of the expectancy (μ) and of the variance (σ^2) of the results of the assembly. This equation is valid for the linear case. The term (ρ_{ij}) describes the coefficient of correlation between the layer *i* and the layer *j*.

$$\mu_{Total} = \sum_{i=1}^{N} \mu_i$$

$$\sigma^2_{Total} = \sum_{i=1}^{N} \sigma_i^2 + 2\sum_{i=1}^{N-1}\sum_{j=i+1}^{N} \rho_{ij}\sigma_i\sigma_j \tag{6.}$$

3 Model Development

3.1 Half cell (HC)

The modeling of the first level is realized according to equation (3.), which allows for the estimation of the average addition of the constituents. Thus, we obtain,

$$\mu_{HC} = \mu_{AL} + \mu_{CAT1} + \mu_{CAT2} + \mu_{SPE1} + \mu_{SPE2} \tag{7.}$$

Next, it is necessary to integrate the variation of the different parameters. As it is no longer possible to consider all the variables as being independent, a corrective factor needs to be added in order to take into account the correlations. Estimating the level of correlation between the various layers is thus crucial. The following table summarizes the different possible correlations.

Table 2. Coefficient of correlation between the various constituents

ρ_{ij}	x_{Al}	x_{SPE_1}	x_{SPE_2}	x_{CAT_1}	x_{CAT_2}
x_{Al}		≈ 0	≈ 0	≈ 0	≈ 0
x_{SPE_1}			$\rho_{SPE_1-SPE_2}$	≈ 0	≈ 0
x_{SPE_2}				≈ 0	≈ 0
x_{CAT_1}					$\rho_{CAT_1-CAT_2}$
x_{CAT_2}					

In the last table, the hypothesis that any correlations between different materials are null was retained. Thus, only the correlation with several layers of the same material is considered. Two correlations will thus be retained at this level. The correlation between the layers of *SPE* and of *CAT* are presented as follows:

$\rho_{CAT_1-CAT_2}$ Is defined as the coefficient of correlation between the thickness of the upper and lower layers of the cathode

$\rho_{SPE_1-SPE_2}$ Correlation between the thickness of the upper and lower layers of the SPE

The calculation of these factors may be done using equation (8.) ,

$$\rho_{ij} = \frac{\sum x_i y_i - \frac{\sum x_i \cdot \sum y_i}{n}}{\sqrt{\sum x_i^{\,2} - \frac{\left(\sum x_i\right)^2}{n}} \cdot \sqrt{\sum y_i^{\,2} - \frac{\left(\sum y_i\right)^2}{n}}} \quad (8.)$$

Special attention must be paid when the data is acquired. To ensure the validity of the estimation of the correlations factors, the measures must be taken at the same location for both the lower and the upper layers. A shift in the taking of the measure would automatically lead to an error in the value of the coefficient. After all the hypotheses, we thus obtain the following equation for the variance of the half-cell (x_{HC}).

$$\sigma^2_{x_{HC}} = \sigma^2_{Al} + 2(1+\rho_{CAT})\sigma^2_{CAT} + 2(1+\rho_{SPE})\sigma^2_{SPE} \quad (9.)$$

3.2 Electrical Cell (EC)

During the last study (of half-cells), the behavior of the variable x_{HC} was modeled. This new variable will be introduced for the study of the current level (electric cell - EC). The modeling is based on equation (2.), and thus we can estimate the average of the new variable using the following equation:

$$\mu_{EC} = N \cdot \mu_{Li} + N \cdot \mu_{HC} + 2 \cdot \mu_{PP} \quad (10.)$$

Next, we need to analyze the variations of this variable. As in the previous case, the independence between variables cannot always be considered for simplifying the study. Indeed, the nature of the process is such that several successive layers stemming from the same lot are directly stacked. This phenomenon, which we indicate in our study as "auto correlation" can have a significant influence on variations if the level of this correlation is large. This phenomenon becomes even more important when there are a significant number of successive layers. The following table demonstrates this phenomenon. We make the same hypothesis during the study of *HC* , in which case there are only minor correlations between the different materials.

ρ_{ij}	x_{HCj}	x_{LIj}	x_{PPj}
x_{HCi}	ρ_{HCij}	0	0
x_{LIi}		ρ_{LIij}	0
x_{PPi}			ρ_{PPij}

Table 3. Coefficient of EC auto correlation

ρ_{HCij} Correlation between the layer (i) and the layer j of the half cell

ρ_{LIij} Correlation between the layer (i) and the layer j of the lithium

ρ_{PPij} Correlation between the layer (i) and the layer j of the polypropylene

These auto correlation factors are estimated using equation 8. With the factors stated above, the behavior of the variation of *EC* can thus be adequately modeled.

$$\sigma_{EC}^{\,2} = n \cdot \sigma_{Li}^{\,2} + n \cdot \sigma_{HC}^{\,2} + 2 \cdot \sigma_{PP}^{\,2} + \rho_{Li} \cdot n \cdot (n-1) \cdot \sigma_{Li}^{\,2} + \rho_{HC} \cdot n \cdot (n-1) \cdot \sigma_{HC}^{\,2} + 2\rho_{PP} \cdot \sigma_{PP}^{\,2} \quad (11.)$$

The last equation thus supports the fact that with a large number of layers, the auto correlation can have a very significant incidence on the variations of the EC. It is more crucial to add the correction factors of the parameters at the level of the EC, and special attention must be paid in order to identify the various coefficients present at this level.

3.3 Study of the battery height

The battery is studied at several levels: the analysis must be realized, taking into account variations of the *Clamp System* in order to allow it to fit into the case (see Fig.2).

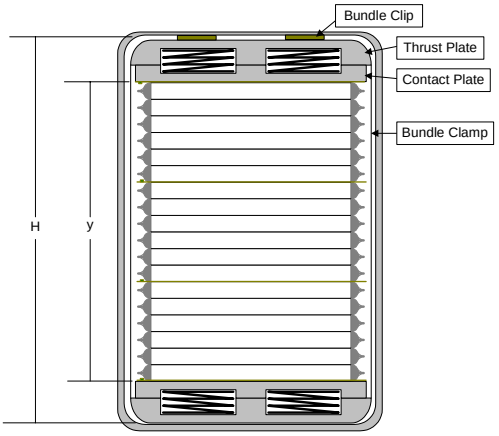

Fig.2. Illustration of the battery assembly

Next, the nominal of "y" must be found and the variations inherent in the ECs calculated. This variation consists of the variation of the processes and of the auto correlation of these defined by the variable (ρ_{EC}).

$$\mu_y = k \cdot \mu_{EC} \tag{12.}$$

$$\sigma_y{}^2 = n \cdot \sigma_{EC}{}^2 + \rho_{EC} \cdot k \cdot (k-1) \cdot \sigma_{EC} \tag{13.}$$

The development of the equations that illustrates all these variations can be described below. (H) is the variable, which defines the dimension of the aluminum case. (CS_{up}) is the addition of the dimensions going from the Bundle Clamp (C) to the outside. This variable thus includes the dimension of the Thrust Plate (TP_{up}) to the outside as well as the dimension of the Bundle Clip (BC). For the variable (CS_{dn}), the reasoning is almost the same, which is the variable of dimensions leaving from Bundle Clamp, but inward. This one includes the dimension of Thrust Plate (TP_{dn}), the dimension of Contact Plate (CP) as well as a space (a) between both. (CS_{dn}) must thus be greater or equal to the height (y) consisting of (k) ECs. Two constraints must thus be simultaneously respected in order to ensure the final insertion.

Constraint 1:

$$\min(H) \geq CS_{up} \tag{14.}$$

$$CS_{up} = \max(C) + 2 \cdot \max(TP_{up}) + \max(BC) \tag{15.}$$

Constraint 2 :

$$y \leq CS_{dn} \tag{16.}$$

$$CS_{dn} = \min(C) - 2 \cdot \max(TP_{dn}) - 2 \cdot CP + 2 \cdot a \tag{17.}$$

4 Numerical Exploitation

4.1. Identification of the model parameters

All the processes used in the manufacture of ECs are *continuous*. The sampling policy is based on the estimation of the correction factors k_i and of the coefficients of correction. It is thus particularly crucial to ensure there is a proper sampling to ensure compliance with the validity of the model. According to the theorem of Nyquist, it is necessary to take at least 2 pieces of data by samples (a sample is considered as in one layer) to be able to detect the variations in the length of the component.

Fig.3. Illustration of acquisitioning data

Another factor which influences the quality of the sampling is the number of given necessary data to assure a good confidence respecting the validity of the sampling. To do so, it is strongly recommended to obtain from 200 to 300 values [14]. We are thus going to proceed as such for each of the parameters to be sought. It should also be noted that for each data collection campaign, an analysis of the measurement system according to the ISO TAG 4 [15] guide was done to ensure an acceptable level of uncertainty of measure.

To identify the correction factors (equations 4 and 5), we proceeded experimentally. For the analysis of charge, a sampling was made to estimate the average contraction due to the discharge of EC. This contraction is attributable only to lithium because the cathode hardly reacts to the charge of ECs. The value of the coefficient is thus distributed only in the lithium. For the coefficient of pressure, the compression of some stacks of ECs was considered in order to establish the value. Through the study, we know from the respective Young modules that we can attribute the major part of the compression undergone by the half-cell to the SPE. The effect of the other materials is considered as negligible. The coefficient due to the thermal expansion was found

with the assistance of a table for the standard materials, and by experiment for the others. The validation of the multiple coefficients was done with the help of a study of an assembly of ECs. For the coefficient k_1, the only possible method was to proceed with an empirical study of the difference between the nominal thickness of a number of laminates and the real thickness of this stack. This coefficient was identified for the assembly, which explains why we have the same value for each of the materials.

Table 4. Coefficients of parameters per element

	$k_1 = k_{rustle}$	$k_2 = k_{temp}$	$k_3 = k_{pressure}$	$k_4 = k_{charge}$
x_{Al}	1.012	1.001	≈ 1.0	1.000
x_{CAT}	1.012	1.013	0.635	≈ 1.0
x_{SPE}	1.012	1.045	0.060	1.000
x_{Li}	1.012	1.003	≈ 1.0	0.940
x_{PP}	1.012	1.006	≈ 1.0	1.000

The second part of this study consisted in validating whether a phenomenon of correlation was significant between two layers of the various constituents. The correlation between two layers of different materials was rejected because their manufacturing processes are completely different.

The only remaining phenomenon was thus the correlation between layers (i) and $(i+1)$ of the same material. To do so, we collected experimental data to establish this correlation. Figure 4 illustrates the results between layers (i) and $(i+1)$ with the cathode as well as with the SPE. Table 5 summarizes the results obtained, which demonstrates that this type of correlation for the studied parameters is not significant.

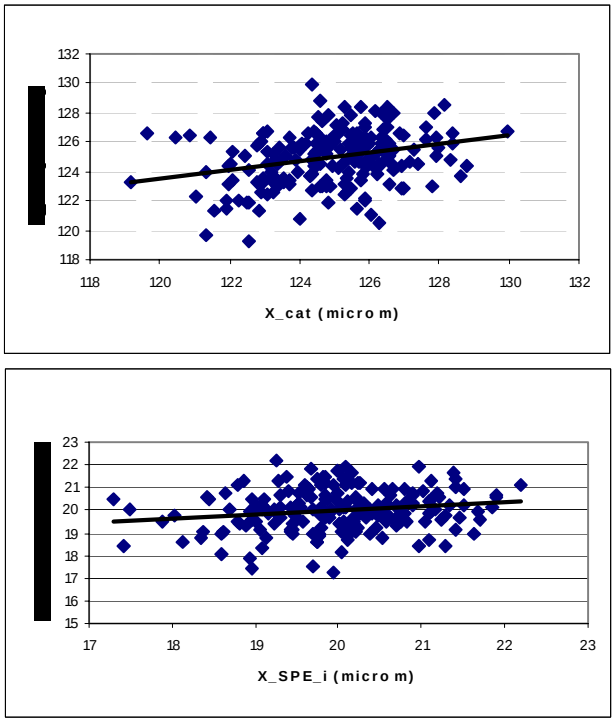

Fig.4. Illustration of the influence of the correlation of the cathode and the SPE

Table 5. Coefficient of correlation between the different components

ρ_{ij}	x_{Al}	x_{SPE_1}	x_{SPE_2}	x_{CAT_1}	x_{CAT_2}
x_{Al}		$\approx$	$\approx$	$\approx$	$\approx$
x_{SPE_1}			≈ 0.12	$\approx$	$\approx$
x_{SPE_2}				$\approx$	$\approx$
x_{CAT_1}					≈ 0.14
x_{CAT_2}					

The third and last part of this experimental investigation was the identification of the auto correlation factor between the various layers of the EC. Each layer arises from an assembly as we saw previously. Data was collected to measure the individual thickness of each EC. The following table illustrates the main results based on the study of this phenomenon for the manufacturing processes of each one. As can be seen, the correlation of the half-cell is relatively weak. Thus, this allows the assignment of a much smaller value for the variation of the final assembly. On the other hand, the auto correlation of the layers of Lithium is more important as it has little effect on the final result due to the low variability of the Lithium extrusion process. Globally, the study allowed us to optimize the design and to assign a larger quantity of active

material in the assembly, thus allowing an increase of the energy efficiency.

Table 6.- Coefficient of EC auto correlation

ρ_{ij}	x_{HCj}	x_{LIj}	x_{PPj}
x_{HCi}	≈ 0.15	0	0
x_{LIi}		≈ 0.8	0
x_{PPi}			≈ 0.5

The simulation of the stochastic behavior allowed us to emphasize the importance of maintaining the level of the auto correlation of the layers of the half-cell (HC) at the lowest possible value. The following figure illustrates the importance of the correlation of the half-cell with respect to the result of the final variation of the assembly. Note that in the case of the statistical study, the level of variation was calculated on the basis of the interval corresponding to 99.73% of the data ($\pm 3\sigma$ or $C_{pk} = 1$).

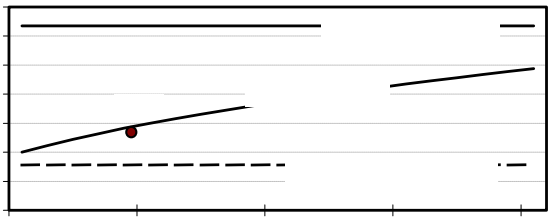

Fig.5. Illustration of the influence of the HC correlation

As shown in Figure 5, it is evident that the correlation of the half-cell is very important for obtaining a precise model. As can be observed, the value of the variation obtained by varying only this parameter can go from 4.00 mm to 9.77 mm. The point, identified by a circle, illustrates the level of variation that corresponds to the experimental data used during this study.

4.2. Numerical Validation

To validate our model and to demonstrate the impact of the correlation and the correctness of the model, a statistical analysis of the historical data (approximately 450 modules) was performed. In each production lot, the coefficients of correlation were identified from the measures done on the production line. The data covers two (2) lamination processes for the lithium. The first process has a coefficient of auto correlation of 0.2 (-----) and the second, of 0.8 (——). Curves indicate the results produced by the model presented in this article. The experimental data connected with the first process of lamination of the lithium are identified by (■) and the data connected with the second process are identified by (●).

The results of the study were then compared with the formula proposed in this article. The graph that follows illustrates the results obtained theoretically and experimentally.

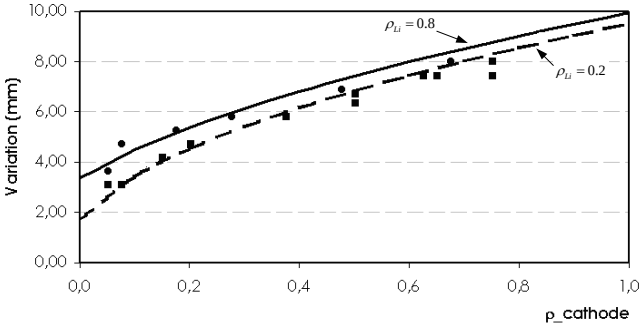

Fig.6. Illustration of the influence of the HC correlation

As can be observed in Figure 6, the theoretical model demonstrates its coherence and its exactness in predicting the global behavior of tolerances. Errors of about 10% remain present in the model. We explain this by some degree of variation of the factor correlations as well as by the variation inherent in the various manufacturing processes of modules. In spite of these variations, it is clear that it is beneficial to take correlation phenomena into account and that the proposed equation constitutes a major contribution to the proper evaluation of the variations for each level of correlation.

Special attention must be paid to the fact that the average of the processes gets closer as possible to the target value. This requirement may be verified through the indication of capability called Cc. This requirement is essential because when a process is correlated, it can have a big influence on the global average of the assembly. This subject will be handled in greater depth in a future paper.

5. Conclusion

The statistical calculation method, taking into account several correction factors was presented in this article. The case study developed an effective method for describing the behavior of a mechanical

assembly composed of multiple layers. The importance of the various correction factors was demonstrated in this article to show their uses. The model so created should very faithfully predict the behavior of the assembly. This method should thus be used for any similar case where the precision of estimations is crucial.

This study allowed the definition of the performances required by the variations of the processes to ensure that the requirements of the design are respected. Recommendations were made for each of the constituents individually in order to obtain maximum results. Furthermore, through a sensitivity analysis, the model allowed the establishment of elements that can bring about maximum earnings. Targeted corrective measures can therefore be brought under the control of the manufacturing processes for the most important elements.

References:

[1] Gilson, J. (1952). A New Approach to Engineering Tolerances. New York, NY: Industrial Press.

[2] Zhang, H. C. (1997). Advanced Tolerancing Techniques (John Wiley & Sons Inc. ed.). New York: Wiley-Interscience.

[3] Srinivasan, V. (April 1997). ISO Deliberates Statistical Tolerancing. Paper presented at the 5th CIRP Seminar on Computer-Aided Tolerancing, Toronto, Canada.

[4] Anselmetti, B. (2000). Cotation fonctionnelle statistique: Modèle et synthèses des tolérances. European Journal of Automation, 345(2-3).

[5] Tahan, A., Songmene, V., Châtelain, J.-F. (2004). Case Study of the Application of Statistical Tolerances Taking Account of Correlation. Paper presented at the Proc. of International Conference on Computers and Industrial Engineering, San-Francisco.

[6] Chang-Xue, F. J., Kusiak, A.,. (2002). Robust Tolerance Synthesis With the Design of Experiments Approach. Transaction of the ASME Journal of Engineering for industry, 122, 520-528.

[7] Cox, N. D., &Shapiro, S.S.,. (1967). Statistical Model in Engineering. Wiley, New York.

[8] Cox, N. D. (April 1979). Tolerance Analysis by computer. Journal of Quality Technology, 11(2).

[9] Björke, O. (1989). Computer -Aided Tolerancing. ASME Press.

[10] Vallée, A., Robillard, C., Wilkinson, H. (2004). The Impact of Lithium-Metal-Polymer Battery. Characteristics on Telecom Power System Design. Paper presented at the INTELEC.

[11] Paradis, R., Simoneau, M., Davis, M.S.,. (2002). Lithium-Metal-Polymer Battery for Stationary Applications. Paper presented at the BATTCON.

[12] Vallée, A., Robillard, C., Wilkinson, H. (2003). The Impact of Lithium-Metal-Polymer Battery. Proven reliability based on customer field trials. Paper presented at the BATTCON.

[13] Cox, N. D. (1986). How to perform statistical tolerance analysis. American Society for Quality Control, 11.

[14] Daimler Chrysler Corporation, F. M. C., General Motor Corporation. (2002). Measurement System Analysis Reference Manual (Third ed.).

[15] ISO. (1993). Guide to the Expression of Uncertainty in Measurement. In. Geneva, Switzerland: International Organization for Standardization.

[16] Lee C.L., Tang, G.R. (2000). Tolerance design for products with correlated characterization.