Chapter 40
Input Analysis in Simulation: A Case Study Based on the Variability in Manufacturing Lines

David Lucas and Alexandra Tenera

Abstract Simulation is a powerful tool with acknowledged capabilities that has proved to be a valuable support instrument to decision making. In order to attain a proper representation from the system, it's necessary to perceptively observe the system, to collect the data corresponding to the model's input, and to perform an accurate analysis of the same data. The results and recommendations subsequent to the simulation are as legitimate as its modeling and inputs. In manufacturing systems build-to-order, that generates multiple products with identical characteristics and high levels of customization, the input analysis earns a vital role. On this article is proposed a methodology to deal with the variability inherent to systems, resorting to statistical inference methods: hypotheses testing. These methods are a vigorous tool on the analysis of data collected from the system. Furthermore, a case study based on a real manufacturing line will be presented, where the impact that the information inputted onto the model has in the simulation's results shall be analyzed, regarding the processing lead time. In addition, the presented case study provides evidence of the two foremost pitfalls, referred by Law, which ought to be avoided. The usage of the mean towards a statistical distribution misleads the system's analyst, whereas the normal distribution doesn't accurately represent the processing times. An adequate replication of the variability over the manufacturing processes from the real system, throughout the probability's distribution on an "off-line" simulation, comprises as a vital element to support decision making.

Keywords Modeling and simulation · Manufacturing lines · Production variability · Statistics

D. Lucas (✉)
Faculdade de Ciências e Tecnologia (FCT), Universidade Nova de Lisboa (UNL), Lisbon, Portugal
e-mail: davidjmlucas@gmail.com

A. Tenera
UNIDEMI, Department of Mechanical and Industrial Engineering, FCT/UNL, Lisbon, Portugal

J. Xu et al. (eds.), *Proceedings of the Eighth International Conference on Management Science and Engineering Management*, Advances in Intelligent Systems and Computing 280,
DOI: 10.1007/978-3-642-55182-6_40,

40.1 Introduction

Simulation is characterized by the customary employment of mathematical and computational models that aid and support the decision-making process. The resort to these models is common when it's impossible or impracticable to perform experiences in the system itself [22]. The construction of a model enables not only to study a system without causing any disturbance on its regular behavior, but it also provides total freedom to test different ideas and solutions [8].

The high complexity verified in the systems currently considered, infers that its computation throughout analytical methods can be inefficient and may depend on an excessive simplification process, questioning the legitimacy of the model. The construction of a model must include an appropriate amount of detail, so that the output and consequent understanding from the model's outcomes may not differ from the potential insights and understanding engaged directly from the system. Consequently, despite simulation not being the only available tool concerning the study of models, it is quite frequently the method chosen to engage in its activity, as it allows the analysis of complex problems [2, 22]. Although its output is not precise, there are ways to deal with its imprecision, to quantify it or to reduce it. It is preferable to obtain an approximate answer to a correct problem than an exact solution to a wrong problem [8].

Ingalls [6] defines simulation as "the process of designing a dynamic model of an actual dynamic system for the purpose either of understanding the behavior of the system or of evaluating various strategies for the operation of the system". The user attempts to infer conjectures from the model to the real system via experimentation. Models are generally simplifications that comprise merely the scope and necessary amount of detail in order to satisfy the goals of the study [22]. By using software conceived to emulate systems' processes and characteristics over time, the model's inputs are numerically exercised and its linkage with outputs is verified, with the aim of determining estimates of the system's performance status.

Jahangirian et al. [7] perform a revision of the application of simulation techniques within industrial sectors, covering articles between 1997 and 2006 and concluding that discrete-event simulation (DES) is the dominant technique concerning simulation's applications over this sector. DES models tend to be suitable to detailed process analysis, resource management or queuing, being that the authors also verified several applications regarding operational management from its planning and production control, to process engineering, inventory management, project management or supply chain, over diversified areas of industry.

DES models have proved to be an excellent tool on the modeling, analysis, and improvement of the production systems' performance. The disclosure of accessible and user-friendly software contributes to the rapid increase of its applications [18].

The current simulation-based softwares available are impressive concerning its range capacity, program capability and sophistication, providing an incomparable support to the development, display and analysis of complex models. Its capacities are the convergence of more the half-century of evolution in software, hardware and simulation's investigation [20]. Swain performs a biannual survey [21] focused on DES based simulators, which according to the author are the most adequate to apply in management and operational sciences. Throughout the years the author has observed and incremental increase on the range and variety of simulators, which is reflected on the strength and robustness of the products, as well as the progressively growing sophistication of its users. To carry out such evolution, it has been important the contribution of aspects such as the improvements introduced on the analysis process, as well as the higher capability to obtain significant replications of a certain experience, which substantially increased the precision verified on statistical indicators, subsequent from the simulation, and the possibility to combine different scenarios. The recently available simulators are increasingly more precise when it comes to respond to problems and in providing solutions.

The optimization of processes and operations on manufacturing systems remains as an important sector on the segment of simulation, which is reflected on the innumerous products available and identified on the survey, concerning the manufacturing sector.

In order to successfully study simulation and attain its consequent validation, it's critical to follow a pre-defined approach that links the construction of the model to a reliable representation of the reality [10]. Skoogh et al. [18] refers that the majority of project's stages concerning this area interacts with the input and output data, being the management of this information the most frequent challenged identified in a simulation project. To this author, the data gathering, analysis and inputs into the simulation model are vital stages within a project.

Also to Biller and Gunes [3] and Kuhl et al. [9], the selection of a valid input is one of the main problems identified in the construction of stochastic models. The modeling of the input consists on the selection of the probability distributions that represent the random variables from the system [3], such as the registered periods of an equipment's failure, or the time between arrivals on a bank. The goal is not to obtain an exact input but an approximation that may capture the key features from each process.

In order to attain a successful simulation, Law [11] identifies two pitfalls to avoid, related with the model's input. The first concerns the frequent substitution of the probability's distribution by its mean, which according to the author may lead to utterly erroneous results, affecting the legitimacy of the outputs. Contrarily to the mean, probability's distributions introduce the variability that regularly occurs on the systems, having a significant effect concerning the traffic in queuing systems. Taking into consideration the distribution's utility in representing the sources of randomness of each system, the second pitfall referred by Law is the persistent utilization of the normal distribution on the model's inputs, being that it is actually rarely adequate to model diverse variations, such as service times, processing times or maintenance operations.

Thus, the choice of a probability's distribution has a large impact on simulation's results and, potentially, on the quality of the decisions taken based on such results. The inadequacy on the choice of the correct distribution affects the model's precision of results, sometimes drastically [2].

The problem in selecting the appropriate input worsens itself on *build-to-order* manufacturing systems, with low volume and high variability, which produce multiple products with high level of customization in each order, as it happens within organizations that produce electrical devises of higher dimensions. These characteristics introduce a great variability over operational processing times. The same operation can extend to for a few hours within a model, and for more than one shift on the next model.

To engage an off-line simulation of a manufacturing line of this kind it's necessary to carefully analyze the model's input to introduce, in order to characterize the variability existing on the system. Just as important as the use of adequate data on the model's construction is the attention to have in structuring the same data. According to Law [10], when several observations are performed to the same event, the homogeneity of data can be evaluated throughout statistical inference tests. If the set of data appear to be homogeneous, the data can be merged and the information can be used to the same purpose on the simulation's model. The manufacturing line's replication through simulation requires simplified models that, yet, can properly represent the reality.

40.2 Problem Statement

Prior to the application of the simulation, in order to promote comprehension, problem solving, process optimization and the study of alternative scenarios on a manufacturing system, it is necessary to gather and analyse the collected data to be able to construct a simple and reliable model. On this case study, it is intended to analyse the processing times of five operations engaged by a corporation that manufactures electrical devices, in order to further perform an off-line simulation, using the software *Arena*, from *Rockwell Automation*.

In organizations in which occurs the production of several products that follow the same manufacturing flow, and in order to properly structure the data and to simplify the simulation's model, it's necessary to verify if there are differences concerning the operation's lengths, according to the processed product. If no differences are verified, the data can be merged and used to represent the existing variability on the process throughout a probability's distribution. Otherwise, it's necessary to find, for each operation, a statistical distribution that can represent the corresponding product's processing time. On the other hand, this analysis enables the organization to determine in which operations are verified greater variability. Furthermore are following described the two main objectives of the presented case study:

1. To verify, throughout processing times, which models are significantly different from one another, in order to be separately modeled in each operation.
2. To adjust the processing times to the statistical distribution that best represents its behavior.

Finally, resorting software *Arena*, it will be examined the first pitfall referred by Law [2]: the frequent replacement of the probability's distribution by its mean. It will be compared the performance of the manufacturing line after introduction of the results brought by the analysis accomplished, with the performance of the same line using merely the mean of the processing times collected for each operation.

40.3 Methodology

In order to characterize the processes' variability over the production line, statistical inference methods are used to further represent it on simulation. One of its most useful applications is the hypothesis tests, whose objective is to verify the plausibility of a particular statement performed. According to Montgomery [13], several engineering tests or experiments involving decisions can be generated through these methods.

The presented hypothesis to be tested, designated Null hypothesis (H_o) must contain an equality which is considered to be truth until a statistical evidence proves it to be wrong. In that case, the alternative hypothesis (H_a), that should contain an inequality, becomes valid. It's essential to highlight that hypothesis are statements about populations or probability distributions studied, and not about samples. Montgomery [13] and Elisabeth Reis [16] developed profounder works concerning this topic.

Nowadays there's a wide variety of hypothesis tests, though in order to select the appropriate test, the type of data collected and purpose of the analysis must be considered for each situation [12]. The analysis of variability in this case-study, achieves the proposed objectives by means of diverse hypothesis tests. In Sect. 40.3.1, a methodology is introduced to perform the comparison of processing times for the diverse products through parametric or non-parametric tests, according to the normality of samples. In Sect. 40.3.2, a method is described for modeling the sources of system randomness through statistical distributions.

40.3.1 Data Structure

To attain a forthcoming characterization of processing times throughout statistical distributions, it's necessary to structure the available data, determining in which processes the operation's length significantly varies with the processed product.

Each set of times from an operation represents a population. In order to determine the population's behavior it's necessary to know its distribution and the value of each parameter. To do so, random samples of the population for each product are obtained, and it is performed a comparison between them, through parametric and non-parametric tests. The goal of this comparison is to verify if the samples can be considered as being resultant from the same population, i.e. if the processing times of a certain operation A don't differ according to the item produced X, Y, or Z.

Table 40.1 Hypothesis tests designated for the comparison of two or more independent samples

	Parametric tests		Non-parametric tests
2 Population	Mean	T-test	Mann-Whitney test
	Variance	F-test	
k Population comparison	Mean	Scheffe test	Kruskal-Wallis test
		HSD Tukey	
	Variance	Bartlett test	

On the majority of statistical procedures it is required the evaluation of normality assumption, being the parametric statistic one of those examples. When the assumption is disrupted, the interpretation and inference may not be trustworthy, or even valid [14].

Although many practitioners and simulation books use and state normal distribution, sources of randomness from manufacturing systems frequently discharge to follow this distribution [2]. If the population's distribution from which the samples were taken remains unknown, the first step to perform a statistical analysis consists in executing a normality test, in order to verify whether if the variable in study follows a normal distribution. In the case it does, the analysis may proceed by resourcing to parametric tests. In the case it doesn't, only the non-parametric tests are liable to be applied.

The cases of acceptance or rejection of the normality assumption have played a central role in many investigation sectors. Consequently, efforts in the creation, development and application of *goodness-of-fit* tests for normality, have been performed throughout the years, which resulted in a wide number of currently available tests and multiple comparisons concerning its power. This discussion currently aids the analyst in performing the adequate choice to each specific situation [17].

According to Razali et al. [15], the most common tests are Kolmogorov-Smirnov (KS), Anderson-Darling (AD), Lilliefors (LF) and Shapiro-Wilk (SW). These four are the foremost tests that are generally available on statistical softwares. Through the comparison of the results obtained over the studies endeavored by Refs. [14, 15, 17] it's possible to conclude that SW test is the most suitable and most consistent option in order to study the normality of the sample. The results obtained from the SW test will determine the application of the following hypothesis tests (Table 40.1).

While engaging in parametric tests, the objective is to study the differences between parameters, mean and variance, from different populations. It is considered that different samples are originated from the same population in case there are no significant differences between their means and variances. Depending on the parameter and number of samples (k) to study, it is selected the most adequate test. In addition, it is assumed that, in regard to comparison tests concerning the mean, the samples are taken from normally distributed populations with equal variances. This assumption primarily involves the execution of the variance comparison test, as shown in Fig. 40.1.

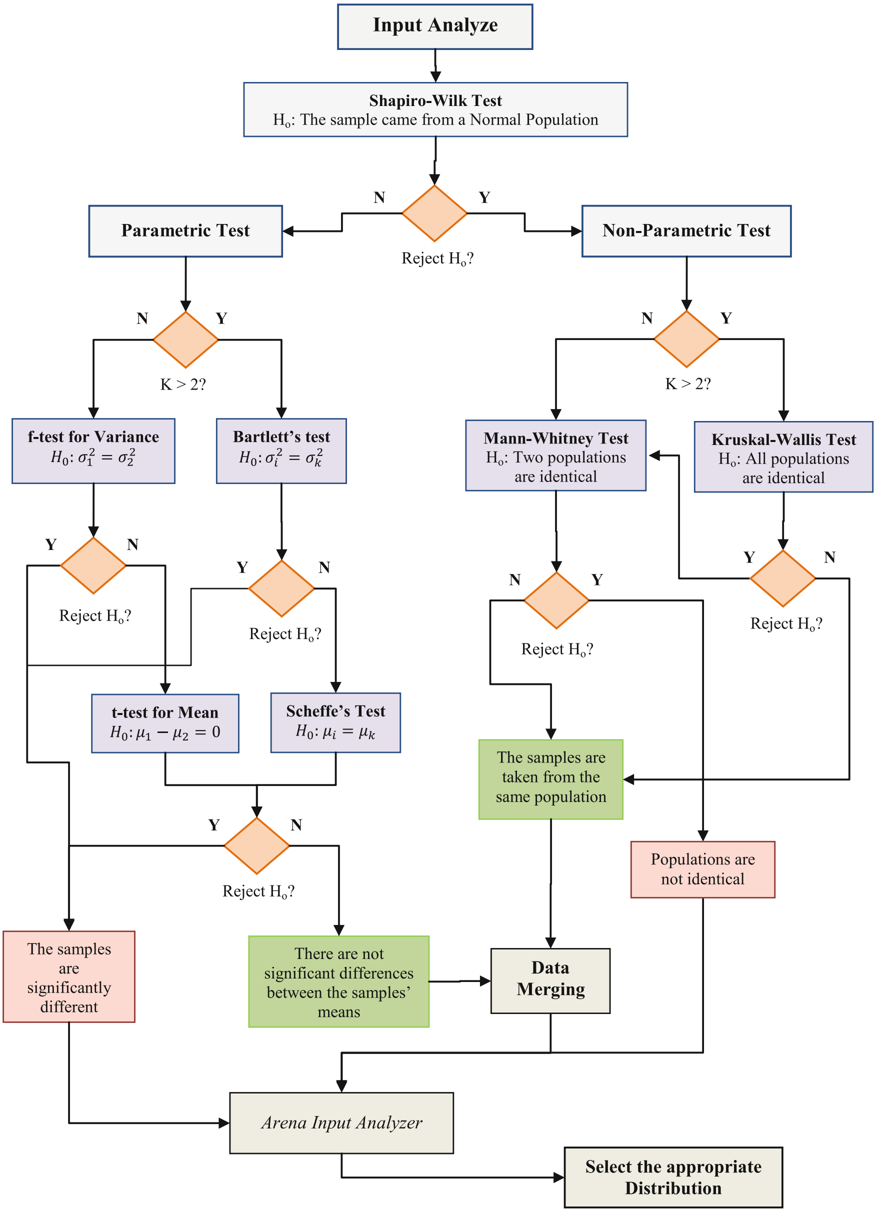

Fig. 40.1 Methodology map

The non-rejection of H_o, concerning these tests, forwards the process into the comparison of means; otherwise it's considered that there are significant differences over the samples' variance and, consequently, infers that the samples were withdrawn from different populations.

From the several tests entailed in comparing the means, the selection resided on the multiple comparison testes, in which the Tukey's HSD test and Scheffe's test are the most frequently used [16]. This tendency is related with the fact that ANOVA merely indicates whether if there are significant differences among analyzed groups, not specifying which group or which linkage between groups verify those differences.

Between multiple comparison tests, Reis [16] gives preference to Scheffe's test, due to its simplicity in the calculation associated, to its consistency in regard to its assumptions, and to allowing the usage of samples with different dimensions.

In the case the test confirms that the samples derive from populations with equivalent means, and knowing that they also possess corresponding variances, it's possible to merge the data and hence it's possible to consider that there are no significant differences between the means of processing times.

On the other hand, in the case that the means of the merged data are significantly different, the processing times of the corresponding models are separately shaped.

Non-parametric methods own its designation to the fact of the entities in study not being the parameters of a population and thus not being necessary to specify the distribution of the corresponding sample, and thus not having to comply with the normality assumption. These methods are generally less powerful and flexible than its homologous parametric methods and therefore, as long as the presuppositions from parametric methods are verified, they should be comprehended as a priority [12]. According to Montgomery and Runger [13] non-parametric tests are less efficient and need samples with larger dimensions in order to reach the same power than parametric methods. However, this difference is not resolutely severe and when the inherent distribution is not normally approximated, these methods are extremely useful.

In these kinds of tests are not performed comparisons in regard to means or variances, being that what's primarily assessed is whether if the shape of the distribution is the same for all samples. To perform a two population comparison test, Montgomery and Runger [13] and McCrum-Gardner [12] recommend the *Mann-Whitney* test, for it is considered to be the non-parametric alternative to t test for differences between means. Finally, in order to compare populations from k independent samples, it must be engaged *Kruskall-Wallis* test, which is a generalization for $k > 2$ samples from the *Mann-Whitney* test.

The rejection of H_o suggests that populations are not identical and it confirms that processing times are directly influenced by the processed model and, consequently, the data can't be merged over the next step. Otherwise, if H_o is not rejected, it means that it doesn't comprise statistical evidence, which infers that the processing times analyzed vary according to the product. Thus data will be merged.

40.3.2 Fit the Statistic Distribution

The assortment of a statistical distribution to a clutch of data can be performed empirically or throughout standard techniques of statistical inference. These techniques consist on the adjustment from several theoretical distributions to the available data, determining the distribution that delivers the closest approximation to the data. According to Law [11], in regard to the empirical approach, only the observed data interval can be generated in the model, which is problematic in case the samples are small. Since is established a theoretical distribution that properly represents the available data, it should be given preference to the statistical inference methods.

In the second part of the statistical analysis it is intended to select the distribution that most accurately represents each set of processing times. This distribution's selection process is currently an important tool for organizations to deal with risks and uncertainties existing among their processes. On the majority of cases, none of the adjusted distributions is precisely correct and thus the goal is to determine the distribution that is sufficiently precise and adequate to the model's purposes [11].

When there is available data, both Biller and Gunes [3] and Law [11] designate three stages to specify a theoretical distribution that may represent the data:

1. Select one or more candidate families of distributions, based on the process's physical characteristics and graphical examination of the data;
2. Estimation of parameters;
3. Check the *goodness-of-fit* via tests and graphical analysis.

According to Kelton et al. [8], the selection of the probability's distribution to apply also depends on the type of data in study. In order to study "Task times", a positive continuous variable, the author indicates as most adequate the distributions Erlang, Gamma, Weibull and Lognormal.

Developing these procedures can be a difficult task, expending a great deal of time and with a will to fall in errors and faults [2], along with the fact that in many of these cases it's complicated to adjust the observed data to less common statistical distributions. For such reasons, the majority of the applications are performed throughout softwares that automatically determine the most accurate distribution adjusted with the data provided. Two frequently used programs that fit this purpose are *Arena Input Analyzer* and *Expert Fit* [4].

Due to the acquaintance with the software, and due to its capabilities to serve the purpose of the present work, the extant case-study was endeavored on the software *Arena, Rockwell Automation*, in order to simulate a production line. Consequently it was resorted the module *Input Analyzer* in order to determine the distribution that most accurately represents the inputted data and its parameters. With the function *"Fit Al"*, the distributions are classified according to its relevancy, based on the values of the corresponding square errors. The selected distribution is then placed into the proper format for direct input in Arena Software.

The module *Input Analyzer*, integrated in Arena software package, also allows the execution of two *goodness-of-fit* tests: *Chi-Square* and *Kolmogorov-Smirnov*. Since the distribution inherent to the studied population remains unknown, the goal of these tests is to study the hypotheses that a certain distribution will fulfill as population model [13].

On the present literature review are studied several *goodness-of-fit* tests, their resultant evolution and numerous comparisons [1, 5, 19, 23]. According to

Kelton et al. [8], there are no conventional and universally established approaches to determine a certain distribution, as for different statistical tests may classify distributions according to dissimilar degrees of relevancy.

The majority of softwares that apply these methods enclose *Chi-Square, Kolmogorov-Smirnov* (KS) and *Anderson-Darling* (AD). Fischer and Kamps [5] compared the power of five *goodness-of-fit* tests and concluded that when statistical values (distribution parameters) differ, the test power differs and consequently the selection of the most adequate test differs along with the results. However, Fisher also states that, in case that only one test is recommended, probably the AD test is the best choice of selection, for it is the most powerful application in several different situations and always the most competitive on situations where it is not the foremost selection. A disadvantage from *Input Analyzer* points out the fact that it doesn't contain the AD test.

40.4 Application/Case Study

The simulation engaged in this study focuses on a production line in which are produced three electrical devices X, Y and Z, with similar characteristics. All three products add up to exactly the same manufacturing flow composed by 5 processes—A, B, C, D and E. The available data employed to analyse the input's variability was collected from a computerized data source from within the company where the results where attained, and comprise the processing times from five years of historical data. After the assembling and validation of the data along with the designated organization, it was initiated an analysis to formulate a set of solutions for both of the problems mentioned in (1) and (2). In order to execute the multiple hypotheses testing, it was used the SPSS software, because it embraces all statistical procedures to apply.

The efforts were initiated with *Shapiro-Wilk* test, being rejected H_o for all samples as observed on Table 40.2, and being able to conclude that no set of processing times belongs to a normally distributed population. Consequently, the effecting of parametric tests was not carried out.

Due to the non-normality of the samples and intending to compare three sets of processing times ($k = 3$), the *Kruskal–Wallis* test was performed. Results revealed that in two processes (B and E) it is not rejected the hypotheses of being identical the populations from which the samples are obtained. Consequently, in these two processes, the length of operations doesn't vary depending on the product, thus the samples are considered to be homogeneous and its data is merged.

When H_o is rejected, it's performed *Mann-Whitney* test to compare each couple of samples, aiming to verify if the variability displayed in the process is particularly caused by any of the products. On process A the distributions of the three samples are significantly different, concluding that the processed item is determinative to the length of the operation. Both in processes C and D, the two products' processing times are homogeneous, being these set of data also merged.

Table 40.2 Results of the statistical tests

	Process A	Process B	Process C		Process D		Process E
Statistical test	X Y Z	X Y Z	X Y	Z	X	Y Z	X Y Z
Shapiro-Wilk	Reject H_a	Reject H_a	Reject H_a		Reject H_a		Reject H_a
Kruskal-Wallis	Reject H_a	Failure to Reject H_a	Reject H_a		Reject H_a		Failure to Reject H_a
Mann-Whitney	Reject H_a	NA	Failure to Reject H_a	–	–	Failure to Reject H_a	NA
	–	Data merging	Data merging	–	–	Data merging	Data merging

Table 40.3 Results from the input analyzer

Production line	Products	Input probability distribution
Process A	X	$4 + ERLA(16.8, 3)$
	Y	$4 + WEIB(37.3, 1.72)$
	Z	$1 + WEIB(22.3, 2.19)$
Process B	X, Y, Z	$4 + WEIB(16.7, 1.8)$
Process C	X, Y	$2 + WEIB(19, 1.48)$
	Z	$1 + LOGN(13, 17.4)$
Process D	X	$10 + WEIB(29.6, 2.22)$
	Y, Z	$10 + GAMM(11.2, 3.26)$
Process E	X, Y, Z	$2 + GAMM(3.34, 5.38)$

On the following stage, each set of data was introduced in *Input Analizer*, which selected the adequate distributed through the less squared error criteria. Throughout *Kolmogorov-Smirnov* test it was able to confirm that the selected distribution is appropriate as a population's model.

The results of these *goodness-of-fit* tests are presented in the shape of p-values, which is the largest value of the type-I error probability that allows the distribution to fit the data. The higher the p-value, the better is the fit. On this study it was rejected H_o to values of p-value smaller or equal to the specified significance: 0.05. The results revealed in *Input Analizer* are shown on Table 40.3.

The analysis performed supports that the information inputted on the model may represent the variability that truthfully exists amongst the manufacturing line. The importance verified on the structuring, as well as the modelling of the data through a probability distribution that represents the system's random variables, are represented on Table 40.4, where can be observed the results of two simulations on the manufacturing line. In Table 40.4 is displayed a comparison between the overall time that products X, Y and Z remain in the system, when are applied the results from statistical analysis (Case I), and when it is inputted the mean of the collected samples in each process from the simulation's model (Case II). It can be verified that in Case II all products remain less time within the manufacturing line. In addition, the mean

Table 40.4 Comparison between processing lead times using sample's mean and using a probability's distribution

Product	Total time in the production line (h)		Percentage of time increased using distributions
	Case I: *a*	Case II: *b*	
X	245.25	217.64	12.69
Y	271.8	220.5	23.27
Z	241.59	218.5	10.57
Total	255.96	219.22	16.76

a: Probability Distribution inputs; *b*: Sample's mean inputs

from the processing lead times is lesser 16,76 % on Case I. This is due to the fact that the normal variations existing among the processes of a manufacturing line are not accounted, misleading the production manager. On the other hand, with an adequate input of the variability from processing times in Case II, the three products take longer in 10 % of the time. In contrast, it can be verified that product Y is the one taking longer to be manufactured. This different is only noticeable after an analysis of the input carried on this case-study.

40.5 Conclusions

The presented methodology, intended to characterize the collected data from a manufacturing line with a high degree of variability, enabled to conclude that the two pitfalls referred by Law substantially affect simulation's results. On the one hand, despite being heavily applied, the normal distribution is not the most appropriate distribution to model many datasets, such as processing times. Throughout *Shapiro-Wilk* test it was confirmed that any sample was correctly described by this distribution. On the other hand, several practitioners frequently replace the usage of a probability's distribution by the value of the sample's mean. Hence, it was possible to conclude that this replacement misleads the analyst because the variability prevailing in the system is not inputted on the model, altering results and thus conducting the manager or person in charge into the risk of carrying decisions that may harm the corresponding organization. To refer that in the present work was used the KS test to engage in the *goodness-of-fit*, due to the fact of being available in ARENA's *Input Analyzer*. However, several studies point out to a greater power concerning Anderson-Darling's test, being this the most adequate choice. The recourse to softwares that include this test, such as *Experfit*, ought to be considered.

Equally important as a correct selection of the distribution that truthfully represents the collected data from the system, is a careful information structuring. Through a sequence of statistical inference tests it was verified that it prevails significant differences regarding the product's processing times, which should be addressed. In addition to a correct input of the information into the model, this analysis enables the organization to verify in which processes comprise higher sources of variation.

The use of statistical methods on the modelling and analysis of the simulation's input is vital, in order to acquire a reliable representation from the system and consequently to attain a high credibility and legitimacy of the simulation's results.

References

1. Arnold TB, Emerson JW (2011) Nonparametric goodness-of-fit tests for discrete null distributions. R J 3(2):34–39
2. Averill M (2007) Law. Simulation modeling and analysis. Tata McGraw-Hill, New Delhi
3. Biller B, Gunes C (2010) Introduction to simulation input modeling. In: Proceedings of the 2010 winter simulation conference (WSC). IEEE
4. Chung CA (2003) Simulation modeling handbook: a practical approach. CRC Press, Boca Raton
5. Fischer T, Kamps U (2013) Power maps in goodness-of-fit testing. Comput Stat 1–18
6. Ingalls RG (2011) Introduction to simulation. In: Proceedings of the 2011 winter simulation conference (WSC). IEEE
7. Jahangirian M, Eldabi T et al (2010) imulation in manufacturing and business: a review. Eur J Oper Res 203(1):1–13
8. Kelton WD, Sadowski RP, Sadowski DA (2002) Simulation with ARENA, vol 3. McGraw-Hill, New York
9. Kuhl ME, Rochester NY et al (2009) Introduction to modeling and generating probabilistic input processes for simulation. In: Proceedings of the 2009 winter simulation conference (WSC)
10. Law AM (2009) How to build valid and credible simulation models. In: Proceedings of the 2009 winter simulation conference (WSC). IEEE, pp 24–33
11. Law AM (2012) A tutorial on how to select simulation input probability distributions. In: Proceedings of the 2012 winter simulation conference (WSC). IEEE, pp 1–15
12. McCrum-Gardner E (2008) Which is the correct statistical test to use? Br J Oral Maxillofac Surg 46(1):38–41
13. Montgomery DC, Runger GC (1999) Applied statistics and probability for engineers. Wiley, New York
14. Razali NM, Wah YB (2011) Power comparisons of shapiro-wilk, kolmogorov-smirnov, lilliefors and anderson-darling tests. J Stat Model Analytics 2(1):21–33
15. Razali NM, Shamsudin NR et al (2012) A comparison of normality tests using SPSS, SAS and Minitab: an application to health related quality of life data. In: International conference on statistics in science, business, and engineering. IEEE, pp 1–6
16. Reis E (2001) Estatística aplicada: probabilidades, variáveis aleatórias, distribuições teóricas
17. Romao X, Delgado R, Costa A (2010) An empirical power comparison of univariate goodness-of-fit tests for normality. J Stat Comput Simul 80(5):545–591
18. Skoogh A, Perera T, Johansson B (2012) Input data management in simulation—Industrial practices and future trends. Simul Model Pract Theory 29:181–192
19. Steele M, Chaseling J (2006) Powers of discrete goodness-of-fit test statistics for a uniform null against a selection of alternative distributions. Commun Stat Simul Comput 35(4):1067–1075
20. Swain JJ (2011) Discrete event simulation software tools: back to the future. OR/MS Today 38(5):56–69
21. Swain JJ (2013) Simulation software survey—Simulation: a better reality? OR/MS Today 40(5)
22. White KP, Ingalls RG (2009) Introduction to simulation. In: Proceedings of the 2009 winter simulation conference (WSC). IEEE, pp 12–23
23. Zhao J, Xu X, Ding X (2010) New goodness of fit tests based on stochastic EDF. Commun Stat Theory Meth 6:1075–1094