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Discrete-Events Simulation for Teaching Statistics in Industrial Engineering

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This paper presents a discrete events simulation tool developed to support undergraduate students in their Statistics and Data Analysis course. Although the use of modern smart technologies in the industry contributes to a profusion of data, very few enterprise datasets are freely available, resulting in a serious lack of open real-world data for research and education. To overcome this difficulty, we designed a tool that simulates scheduling scenarios in a manufacturing environment. The generated data may be used to put statistical concepts and methods into practice to design cost-effective strategies for optimizing key performance indicators, such as reducing production time, improving quality, eliminating wastes, and maximizing profits.

Keywords: *industrial datasets, teaching statistics, discrete events simulation*

Introduction

Industrial engineering (IE) is the branch of engineering that deals with improving processes, systems, or organizations and designing goods or services in the most efficient way possible, saving money, time, raw resources, labor, and energy while complying with safety standards and regulations. Industrial engineers use scientific and technical knowledge and skills to integrate and operate complex systems, and as such, their training programs have a significant scientific component. IE educators appear to agree on IE knowledge and curriculum structure while continually seeking innovations in content and instruction (Lang et al. 1999, Davies 2001, Carrera 2006, Eskandari et al. 2015, Lima et al. 2012, Sackey and Bester 2016). In comparative studies, there is consensus that statistics and data analysis are part of the core courses in IE programs, and contextualizing learnings by working with realistic data is highly recommended to help students better understand their future profession (Kuo 2001, Fraser and Teran 2006, Nguyen and Nguyen 2018).

Five main features of authentic contexts have been proposed (Cobb 1999, Fosnot 1996, Tynjala 1999), and they provide a theoretical justification for the inclusion of realistic contexts in teaching and assessment processes (Libman 2010): 1) *practical significance*: Lave and Wegner (1991) argue that knowledge is situated and contextual and, therefore, the material studied must be related to real situations in which students are likely to use it; 2) *complexity and challenge*: in real life, events always present a wealth of data and conditions that can be studied

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from different angles and approached from multiple perspectives. Mirroring this, a learning situation that encourages personal investigation in a realistic context is rich and complex; it does not prescribe a single correct way of learning about reality or a single correct answer (Kirschner et al. 2006). Students are challenged and respond by formulating their own questions, developing their own models and explanations, and examining their own results (Garfield and Ben-Zvi 2007); 3) *relevance and motivation*: relevance refers to the fact that if the context is meaningful enough for the learner to appropriate it, then she or he can harness her or his energy to invest what is necessary to acquire a deep understanding of the subject matter and readiness to use it (Driver et al. 1994); 4) *interconnectedness and transfer*: this argument concerns the importance of authentic context in using the learned material to solve new problems and empower the learner. With real-life data, students learn significantly more about how to figure out an appropriate combination of rules for each new problem and how to use it for problem-solving (Gergen 1995, Hmelo-Silver 2004); 5) l*earner empowerment*: teaching and assessment processes that encourage personal investigation in a realistic context enhance the role of the learner (Eisner 1999, Graves 2002). Because students know the situation they are studying, they become somewhat experts and can take the initiative, raise questions and issues, and bring up topics for discussion with the teacher or their peers. In this way, they acquire knowledge that can go beyond the topic under investigation.

Consistent with these considerations, a large body of research has been conducted to improve the educational experience of statistics students, and they agree on the added value of using real-world data (Willett and Singer 1992, Scheaffer 2001, Bryce 2005, Russell et al. 2011). There is general agreement that statistics are taught more effectively using real-world data (Cobb and Moore 1997), and some research suggests that students consider the use of real-world datasets to be relevant to learning, interesting, motivating, promoting greater involvement and engagement, and lending itself to greater understanding (Neumann et al. 2013). In addition, the use of real-world datasets gives the learning experience a more personal character that increases interest in learning (Chottiner 1991). However, presenting applied problems in a course does not automatically increase motivation; what is essential is how students work with real-life data. According to (Biggs and Tang 2011), students are motivated if they perceive their task as reasonable and beneficial in some way. They should find the task useful for understanding the theory, for the exam, or for their future professional life. In addition, data collection by students themselves has an increased benefit to learning (Hogg 1991).

In their search for realistic contexts, instructors generally use actual real-life data, simulated data, or data derived from real-life datasets by simulation (Luse and Burkman 2018). A major problem with real-world data is that it is not freely available for teaching and research. For example, in the IE field, we could take advantage of the large amounts of data produced by companies driven by digital transformation and the increasing use of connected devices and interconnected machines. However, as this data is at the heart of manufacturing systems, it is rarely shared or freely available, resulting in a serious lack of real open data for research and education. Various simulation tools have been developed to overcome this difficulty, some of which are free[1], to generate data that has the complexity and nuances of actual real-world data.

To support IE undergraduate students at the University of South Brittany (France) in their one-semester course on statistics and data analysis, we developed a simulation tool in the agri-food domain. It simulates the operation of a pastry factory based on discrete-events simulations (DES) (Elizandro and Taha 2007). Simulation models are usually built to understand how systems behave over time and compare their performance under different conditions. DES models are widely used for design and implementation tasks, operational analysis, advanced planning, resource allocation, and logistics management. They are also commonly used for scheduling and automation, at the heart of Industry 4.0 (Ram and Davim 2018).

The main objective of our simulation tool is to create realistic industrial experiments and data to put into practice data analysis methods (sampling, confidence intervals, hypothesis testing, regression models). Our tool considers the parameters and data formats that students encounter most in their professional lives. The input parameters of the simulator are typical of the ERP (Enterprise resource planning) data, and the outputs are typical of the SCADA (Supervisory control and data acquisition) feedback. The simulated data can be used, among others, to (1) identify the most significant key performance indicators (overall equipment effectiveness, capacity…) through the analysis of production behavior; (2) determine critical phases of the production process and understand the involvement of the physical environment in the quality of production.

We use this tool to practice the concepts studied in the Statistics and Data Analysis course, namely descriptive statistics, confidence intervals, hypothesis testing, and linear and logistic regression models. Following the approach studied by (Gratchev and Jeng 2018) and applied by (Carr M, Fhloinn 2016, Farell and Carr 2019), we use a "hybrid" pedagogical approach. We present the basic concepts in statistics and probability in the traditional approach in class, and then a project is introduced to consolidate the theory covered while allowing students to apply it in realistic situations. For the project, students work in small groups of 2 or 3 on datasets generated by the simulation tool, one per group. Students must formulate practical questions that they answer using the statistical methods studied. Real-world statistical projects aim to improve students' understanding of the material and help them develop their problem-solving, teamwork, and oral and written communication skills.

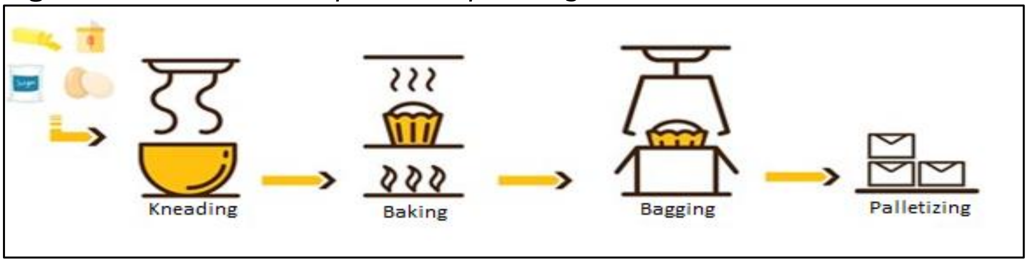
The paper is organized as follows: in the next section, we describe the simulated manufacturing system, followed by a section on how we designed the simulation tool and the experiments it allows. In the "Results Analysis Framework" section, we present an experiment, some simulated results, and their use in the student project. We conclude with a discussion and some perspectives.

[1]https://en.wikipedia.org/wiki/List_of_discrete_event_simulation_software.

The Manufacturing System

The manufacturing system in focus includes the four main activities shown in Figure 1. Various raw materials (eggs, butter, sugar, flour) are mixed and kneaded to form a dough shaped into pastries and baked in batches in an oven. Once cooked, the pastries are packed and palletized. Quality control takes place after the bagging phase; it consists in testing a random sample of pastries from a lot and deciding whether to accept or reject the whole lot based on the quality of the random sample.

Figure 1. *Main Activities of the Manufacturing Process*



There are many factors involved in performing the activities, and a disruption in any one of them affects the rest of the process. For example, a stopping during baking results in under-baked or over-baked pastries and their subsequent disposal, which, in turn, affects the number of packaged, palletized, and sold products.

According to Schruben and Schruben (2001), the rules or factors that govern the interaction of entities in a system are called parameters if they cannot be controlled and laws if they are controllable. Figure 2 shows some of the parameters and laws of our manufacturing system; one can refer to Table 1 for a list of the main factors.

Figure 2. *Manufacturing System*

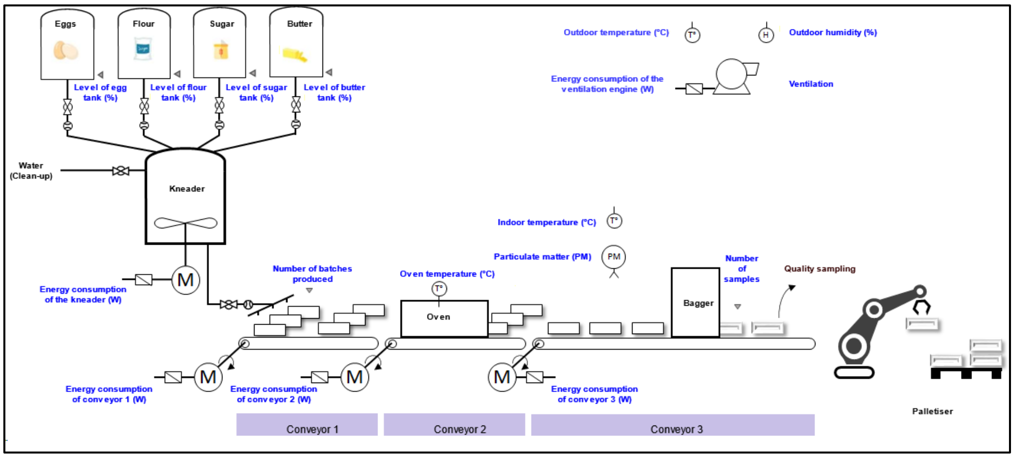


Table 1. *Main Manufacturing System Factors*

Equipment shutdown by equipment (0, 1)
Equipment failure by equipment (0, 1)
Oven temperature (°C)
Amount of each ingredient needed to make a lot of pastries (% of the tank size)
Number of rejects during a run
Level of each ingredient tank during production (%)
Maximal level of each ingredient tank
Maximal refill time for each ingredient tank (seconds)
Minimal refill time for each ingredient tank (seconds)
Refill time for each ingredient tank during production (seconds)
Maximal number of staffers
Minimal number of staffers
The actual number of staffers
Time spent in the oven (min)
Time spent on the conveyor 3 (min)
Quality of the sampled items
Disposal thresholds
Random disposal thresholds

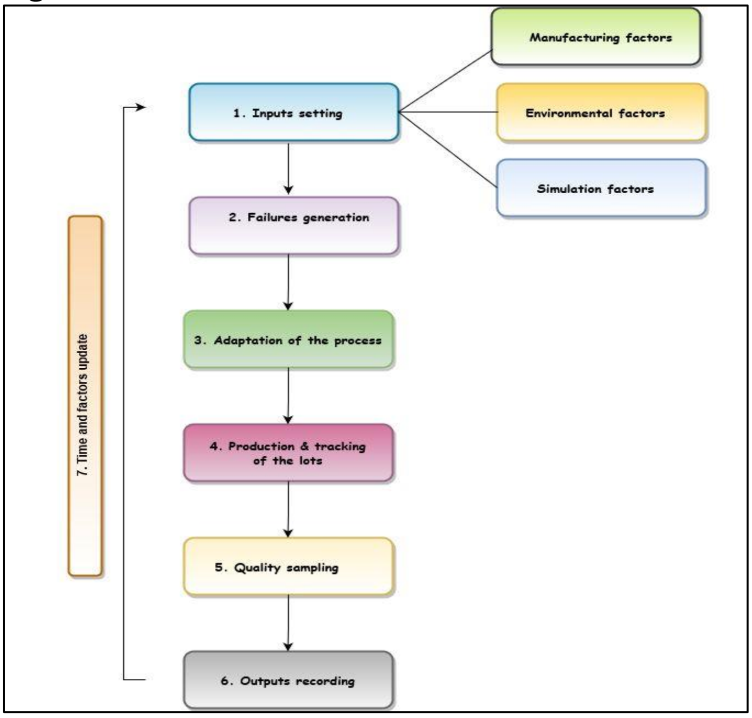
The Simulation Tool

A manufacturing system is a combination of resources (machines, people, raw materials...), planning, organizational structures, information flows, and IT-systems that aim to achieve the manufacture of an economic product cost-effectively. To understand how systems behave over time and to compare their performance under different conditions, two types of simulation models can be built: (1) discrete-event dynamic system models where the operation of the system is represented as a chronological sequence of events, and (2) continuous-event dynamic systems that track systems responses over time according to a set of equations involving usually differential equations.

We adopted the discrete-event simulation (DES) approach which is generally used to model workflow as a network of queues and activities where state changes occur at discrete and irregular time stamps. DES models are generally stochastic, and randomness is generated using statistical distributions.

The general framework of the simulation is depicted in Figure 3. It proceeds in the following steps for a single run: (1) the user selects a combination of input factors related to the manufacturing system, the environment, and the simulation. (2) depending on the stated inputs, a variety of failures can be generated. These can be random or functional (they follow statistical distributions). In case of failure, an intervention request is launched. It feeds a knowledge base of failures and repair response times according to the type of failure, the number of available staffers, and the failure time occurrence (hour, day, month). (3) The laws of the industrial process are adapted to the inputs and, (4) the production process is launched. (5) An assurance sampling is carried out; it consists of selecting some items in a lot and deciding whether to accept or reject the entire lot based on the inspection of the sample. (6) The output data are stored in a spreadsheet (CSV file) for subsequent statistical analysis: one line per run. (7) the simulation tool updates the input settings for a new run.

Figure 3. *Simulation Framework*



The factory's operation can be simulated over long periods - up to one year - with a time increment of one minute at least. Table 2 describes the main factors involved in the simulation process at different stages.

The simulation outputs are provided in Table 3. Among them is the production quality indicator which is calculated as a linear combination of 5 stochastic quality indicators: 1) a baking quality indicator which corresponds to the time spent by a batch of pastries in the oven. It follows a Gaussian distribution around a theoretical baking time with a given standard deviation; 2) an error function that ensures that products that have been in the oven for a long time are not systematically rejected if the oven is at low temperature; 3) a Humidex[2] index which combines temperature and humidity in one computed value. The higher the Humidex, the softer the cakes and the more mold can develop. Conversely, if the Humidex is too low, the cakes are too dry and therefore of poor quality; 4) a ppm quality indicator which corresponds to an error function that reflects the quantity of particles suspended in air; 5) a cooling quality indicator which corresponds to an error function that reflects the time spent by a batch of pastries between the oven and the bagger; this is a critical time during which bacteria can grow. Production quality is

[2]https://en.wikipedia.org/wiki/Humidex.

a standardized metric with values ranging from 0 to 1. The closer the value is to 1, the higher is the production quality.

The simulation tool was implemented in Python 3.6 with standard libraries.

Table 2. *Main Simulation Factors*

Time	Start date of the simulation: parameter
	Simulation during weekends (yes, no)
	No simulation on Friday afternoons for clean-up (yes, no)
Failure generation	Failure simulation (yes, no)
	Time occurrence
	Number of runs before failure per equipment
	Repair response time per equipment
	Range of the response time per equipment
	Range of the random failures per equipment
Sampling	Sampling range per hour of operation
Outputs	Recording of the data (yes, no)
	Recording increment (day, minute)
Environment	Indoor and outdoor temperatures (°C)
	Outdoor humidity (%)
	Particulate matter (ppm)
	Range of particulate matter when the fan is on (ppm)
	Thresholds that set the increase and decrease of the indoor temperature (°C)
Production	Theoretical time to produce a lot (seconds)
	Number of pastries in a lot
	Weight of a pastry (g)
	Number of lots produced during a run
	Theoretical power consumption per engine equipment (W)
	Thresholds for PID and engine power consumption (W)
	Refill time for raw material tanks (min)
	Temperature thresholds for fan operation (°C)
	Thresholds for increase and decrease of indoor temperature and particulate matter
	Thresholds for baking quality indicators, humidity index, ppm quality indicator, cooling quality indicator

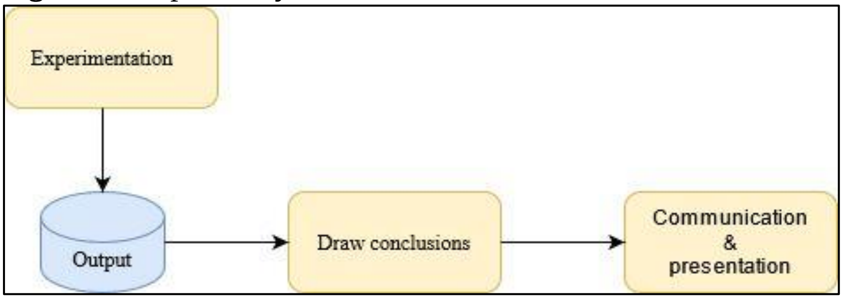
Table 3. *Output Variables*

Categorical variables	Continuous variables	Discrete variables
Day and Daytime	Weekly production load: %	Number of staffers
Equipment Failure (oven, kneader, bagger, fan, conveyors): yes, no	Equipment downtime (oven, kneader, bagger, fan, conveyors): min	Number of lots produced
	Energy consumption per equipment (oven, kneader, bagger, fan, conveyors): W	Number of samples
	Production quality indicator	Number of rejects
	Tank level per ingredient (egg, flour, butter, sugar): %	
	Outdoor temperature: °C	
	Indoor temperature: °C	
	Outdoor humidity: %	
	Oven temperature: °C	
	Particulate matter: ppm	

Output Analysis Framework

After designing a simulation model and implementing a corresponding program, appropriate output analyses must be performed. As shown in Figure 4, the main activities related to analyzing output data are experimentation, drawing reliable conclusions, communication, and presentation.

Figure 4. *Output Analysis Framework*



When setting up the simulation experiment, it is necessary to choose the type of simulation to perform. There are generally two types of simulations: terminating and non-terminating. The difference between them is whether one is interested in the system's behavior over a given period (final production counts, time-changing behavior) or in the steady-state behavior of the system (overall average behavior). Experiments involving terminating simulations are typically conducted by running multiple simulations, or replications, of the period of interest using a different random seed for each run. This procedure allows for statistically independent and unbiased observations of the system response over the simulated period. The three questions that need to be answered when running a terminating experiment are: what the model's initial state should be, the terminating event or time, and how many replications to do.

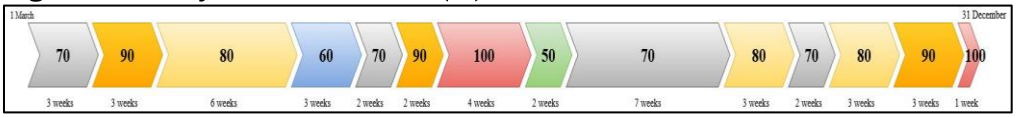
The problems associated with producing meaningful output statistics for terminating simulations are different from those for non-terminating systems. In steady-state simulations, we face the following problems: determining the initial warm-up period, choosing among several alternative methods for obtaining sample observations, and determining the run duration.

In the context of our course, we were interested in terminating simulations.

Cases of Study

We simulated ten months of operation of the factory, from 1 March to 31 December. The weekly production load during the simulated period is given in Figure 5. For example, from 1 March to 21 March inclusive, the production load per week was 70%.

Figure 5. *Weekly Production Load (%)*



Quality sampling was carried out every two hours, starting at 00:00 for 13 minutes. In the following, we introduce the categorical variable Daytime which refers to the sampling periods (cf. Table 4).

Table 4. *Categorical Variable Daytime*

Sampling period	00:00 00:13	02:00 02:13	04:00 04:13	06:00 06:13	08:00 08:13	10:00 10:13
Daytime	0am	2am	4am	6am	8am	10am
Sampling period	12:00 12:13	14:00 14:13	16:00 16:13	18:00 18:13	20:00 20:13	22:00 22:13
Daytime	12am	2pm	4pm	6pm	8pm	10pm

We recorded 3762 entries, one per sample, and for each sample, the variables in Table 4 were filled in.

In what follows, we answer two questions raised by the students regarding the simulated data using some of the methods studied in the Statistics and Data Analysis course. All analyses were performed in R, a free data analysis software (R Core Team 2021). Assumptions' validity is always checked prior to performing the tests; however, we present them after the results for convenience.

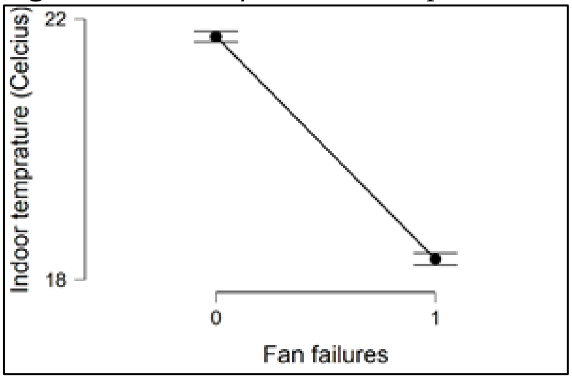
Question 1: What is the impact of fan failures on the factory's indoor temperature and particulate matter?

Temperature

We used a two-sided independent t-test to determine if there is a statistical difference between the average indoor temperatures in case of fan failure (N_1=2148, m_1=21.73, s_1=1.93) versus no fan failure (N_2=1524, m_2=18.32, s_2=1.83). We found out that fan failures significantly increase the indoor temperature of the factory ($t(3670)$=53.95, p<0.001). Cohen's d (1.81) suggests that this is a large effect. The 95% confidence interval (CI) for the difference between temperature means is 3.29°C - 3.54°C and it suggests that the true increase in temperature means is likely to be within this range 95% of the time. Figure 6 depicts the 95% CIs of the indoor temperature by fan failure occurrence; the centers of the CIs are connected by segments for better graphical readability.

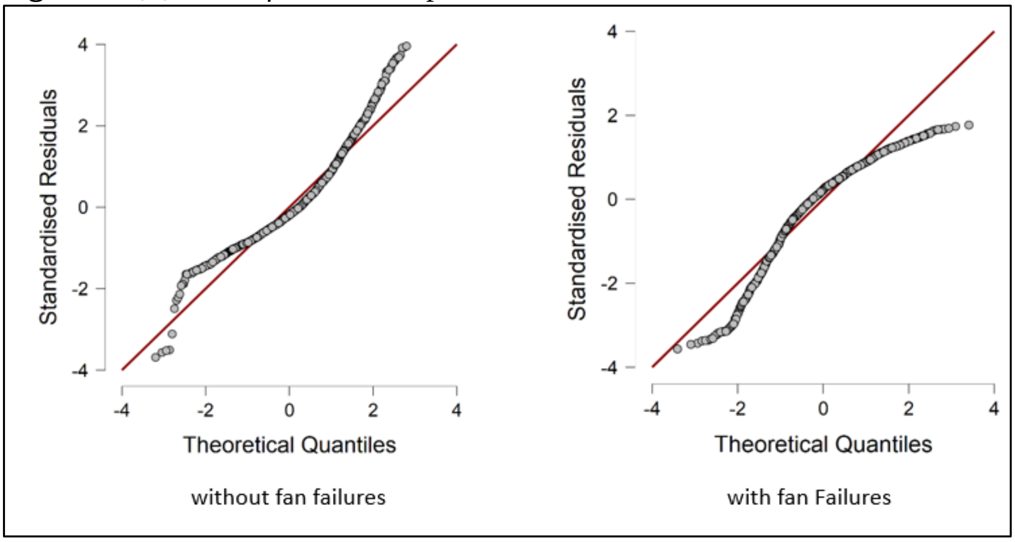
The assumptions of the independent t-test require: (1) independence of the two groups (with and without fan failures groups are independent); (2) the dependent variable should be approximately normally distributed in each group. The QQ-plots in Figure 7 show deviation from normality of the two distributions, which is confirmed by Shapiro-Wilk tests (without fan failures: W_1=0.93, p<0.001; with fan failures: W_2=0.92, p<0.001). However, we have very large sample sizes, and we can still use t-tests; (3) homogeneity of variance is tested using Levene's test of comparison of variances and it showed no difference between the variances of the two groups.

Figure 6. *95% CIs for Indoor Temperature*



Note: 0 and 1 stand for “without” and “with” fan failures respectively.

Figure 7. *QQ-Plots of Indoor Temperature*

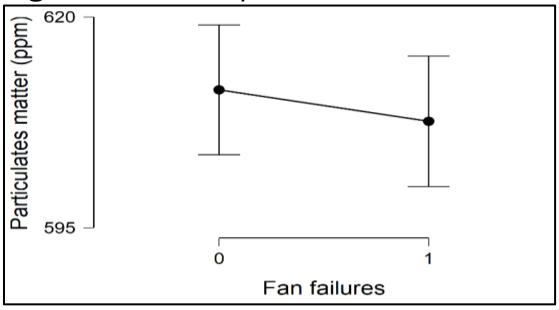


Particulate Matter

We used a two-sided independent Welch’s t-test to compare the average indoor temperatures in case of fan failure (N_1=2148, m_1=611.36, s_1=181.99) versus no fan failure (N_2=1524, m_2=607.63, s_2=154.19). There is no evidence of an effect of fan failures on the amount of particulate matter in the air (t(3556.7)=0.67, p=0.50 ns); Figure 8 shows the large overlap of the 95% confidence intervals of the two groups.

Shapiro-Wilk tests showed a normality violation of indoor temperature in each of the two groups (without fan failure: W_1=0.91, p<0.001; with fan failure: W_2=0.97, p<0.001). In addition, Levene’s test showed a significant difference between variances. We accounted for these violations using the adjusted Welch’s t-test statistic, which is robust for skewed distributions and large sample sizes.

Figure 8. *95% CIs for Particulate Matter*



Note: 0 and 1 stand for "without" and "with" fan failures respectively.

Question 2: Does the production quality indicator change over time and is it affected by the weekly charge load?

Tables 5 and 6 provide descriptive statistics of the production quality indicator by weekly charge load and daytime respectively. Differences in average quality scores can already be observed by weekly load and over time. It is yet to investigate whether these differences are significant and whether there is an interaction effect between the weekly production load and the sampling timetable.

Table 5. *Production Quality Indicator by Weekly Production Load*

	Weekly charge load (%)					
	50	60	70	80	90	100
Sample size	504	252	839	1008	672	393
Mean	0.87	0.77	0.89	0.85	0.85	0.78
Std. Deviation	0.07	0.05	0.08	0.09	0.09	0.07
Minimum	0.63	0.57	0.60	0.57	0.53	0.60
Maximum	0.98	0.91	0.98	0.98	0.97	0.96

Table 6. *Production Quality Indicator over Time*

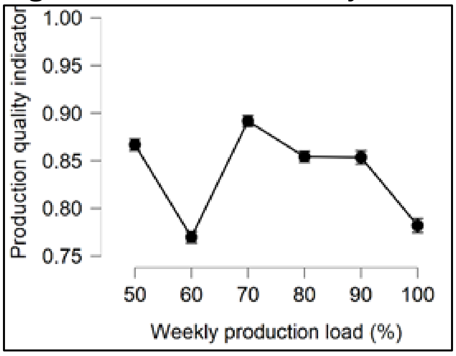
	Daytime											
	0am	2am	4am	6am	8am	10am	12am	2pm	4pm	6pm	8pm	10pm
Sample size	305	306	306	306	306	306	306	306	305	305	305	306
Mean	0.86	0.86	0.84	0.85	0.87	0.86	0.84	0.84	0.87	0.86	0.83	0.84
Std. Deviation	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
Minimum	0.63	0.63	0.60	0.64	0.60	0.61	0.61	0.57	0.60	0.57	0.63	0.53
Maximum	0.98	0.97	0.96	0.97	0.98	0.97	0.96	0.97	0.98	0.98	0.96	0.96

A two-way independent Anova (Analysis of variance) was conducted to examine the effect of the weekly production load and daytime on the production quality indicator. There were significant main effects for both weekly production load ($F(5{,}3595)$=147.62, p<0.001) and daytime ($F(5{,}3595)$=6.51, p<0.001). There was no evidence of an interaction effect ($F(55{,}3595)$=0.26, ns). Omega squared measure suggests a large main effect of the weekly production load (ω^2=0.17) and a small effect of daytime (ω^2=0.014). After checking Anova's assumptions, we carry out post hoc testing to go further.

Effect of the Weekly Production Load

Figure 9 depicts the behavior of the production quality according to the weekly production load; p-values and confidence intervals are adjusted for comparing a family of 6 estimates using Tukey's correction method. The centers of the confidence intervals are connected by segments for better graphical readability.

Figure 9. *Production Quality Indicator by Weekly Production Load*



We observe that the best quality scores are achieved for a weekly production load of 70% and the lowest for 60% and 100% loads. These findings are confirmed by Tukey's pairwise comparisons which are summed up in Table 7.

Table 7. *Tukey's Post Hoc Comparisons - Weekly Production Load (%)*

Weekly Production Load (%)		Mean Difference	95% CI for Mean Difference		t	p_{tukey}	
			Lower	Upper			
60	50	-0.10	-0.12	-0.08	-15.20	< 0.001	***
	70	-0.12	-0.14	-0.10	-20.49	< 0.001	***
	80	-0.08	-0.10	-0.07	-14.47	< 0.001	***
	90	-0.08	-0.10	-0.07	-13.70	< 0.001	***
70	50	0.02	0.01	0.04	5.32	< 0.001	***
	80	0.04	0.03	0.05	9.69	< 0.001	***
	90	0.04	0.03	0.05	8.89	< 0.001	***
	100	0.11	0.10	0.12	21.66	< 0.001	***
100	50	-0.08	-0.10	-0.07	-15.22	< 0.001	***
	80	-0.07	-0.09	-0.06	-14.65	< 0.001	***
	90	-0.07	-0.09	-0.06	-13.60	< 0.001	***

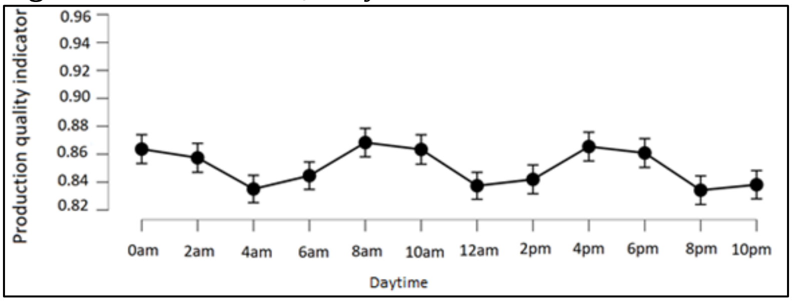
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Note: Results are averaged over the levels of Daytime.
Note: The pairwise comparisons that are not presented are non-significant.

A low-quality score for a 100% production load can be understood by the fact that higher workloads lead to higher equipment utilization and therefore higher risk of breakdowns and sub-quality. On the other hand, such a low score for a 60% workload should raise questions and call for investigations to find potential sources of problem and correct them.

Effect of Daytime

Figure 10 depicts the evolution of the production quality over time; p-values and confidence intervals are adjusted for comparing a family of 12 estimates using Tukey's correction method.

Figure 10. *Production Quality Indicator over Time*



One can observe that the best quality scores are achieved for 0am, 8am, 10am, 4pm, and 6pm, and the lowest for 4am, 12am, 8pm, and 10pm. These findings are confirmed by Tukey's pairwise comparisons which are given in Table 8.

Table 8. *Tukey's Post Hoc Comparisons – Daytime*

Daytime		Mean difference	95% CI for mean difference		*t*	p_{tukey}	
			Lower	Upper			
4am	0am	-0.03	-0.05	-4.13e-3	-3.82	< 0.01	**
	8am	-0.03	-0.06	-7.79e-3	-4.32	< 0.001	***
	10am	-0.03	-0.05	-3.53e-3	-3.74	0.01	*
	4pm	-0.03	-0.05	-5.85e-3	-4.05	< 0.01	**
	6pm	-0.03	-0.05	-2.46e-3	-3.60	0.02	*
12am	0am	-0.03	-0.05	-2.10e-3	-3.55	0.02	*
	8am	-0.03	-0.05	-5.77e-3	-4.04	< 0.01	**
	10am	-0.03	-0.05	-1.51e-3	-3.47	0.03	*
	4pm	-0.03	-0.05	-3.83e-3	-3.78	< 0.01	**
	6pm	-0.02	-0.05	-4.37e-4	-3.33	0.04	*
8pm	0am	-0.03	-0.05	-5.72e-3	-4.04	< 0.01	**
	8am	-0.03	-0.06	-9.38e-3	-4.53	< 0.001	***
	10am	-0.03	-0.05	-5.13e-3	-3.96	< 0.01	**
	4pm	-0.03	-0.06	-7.44e-3	-4.27	< 0.01	**
	6pm	-0.03	-0.05	-4.05e-3	-3.81	< 0.01	**
10pm	0am	-0.02	-0.05	-2.90e-4	-3.31	0.04	*
	8am	-0.03	-0.05	-3.95e-3	-3.80	< 0.01	**
	4pm	-0.03	-0.05	-2.01e-3	-3.54	0.02	*
2pm	8am	-0.03	-0.05	-2.74e-3	-3.64	0.01	*
	4pm	-0.03	-0.05	-7.97e-4	-3.38	0.04	*

* p < 0.05, ** p < 0.01, *** p < 0.001
Note: Results are averaged over the levels of Weekly production load.
Note: The pairwise comparisons that are not presented are non-significant.

To conclude, the two case studies presented here illustrate some practical uses of the simulation tool in a statistics and data analysis course. We have covered some descriptive and inferential statistics topics: confidence intervals, normality tests, t-tests, homogeneity tests, Anovas. However, the diversity of the output variables (continuous, discrete, categorical) allows for more analyses (linear regression, logistic regression, multiple component analysis, and more). Another advantage of this tool is generating custom datasets to focus on a particular technique and explore its many facets.

Discussion

The simulation tool has not yet been evaluated in the Statistics and Data Analysis course. However, it was evaluated in the Advanced Management course, where it was used in hands-on work for building production indicators and improving production. Student feedback was positive regarding the industrial context of the project and the manipulation of real-world data. A qualitative analysis of the added value of the simulation tool and a rigorous quantitative analysis of the knowledge and learning gains still need to be done in both courses.

Eventually, the simulation tool will be used in several courses and at different levels of student training: in the first year for statistical analysis of data, in the second year for the optimization of manufacturing processes, and the third year for the drafting of specifications, technical and commercial communication materials, Etc.

As for future developments of the simulation tool, randomness is currently generated by uniform and Gaussian distributions, and we plan to introduce other statistical distributions for specific events (Exponential and Erlang for inter-arrival times, triangular, beta, normal, and LogNormale for service times, Weibull for inter-arrival times, Etc.) We also need to develop a user interface that will allow students to design their own data sets and quality indicators.

Conclusion

We believe that when students are actively involved in an experiment, they internalize better the material being taught and mobilize more inner resources for learning. The industrial context could help to get more commitment of the students by projecting them in their future profession and following that, to adopt a professional posture in the analysis of the problem, the choice of the data analyses to carry out, their rigorous application, and the restitution of the results in a form that is clear, concise, and adapted to the recipient.

In this vein, we proposed a simulation tool to generate realistic industrial datasets and we presented two case studies to illustrate its use in a Statistics and Data Analysis course for IE undergraduate students. The case examples focused on some common concepts in descriptive and inferential statistics. However, the diverse nature of the output variables allows for a wider range of analysis techniques.

The simulated data can serve the analysis of the production behavior of manufacturing systems and the identification of the most significant key performance indicators (overall equipment effectiveness, capacity...). They can also be used to identify the critical phases of the production process and to understand the involvement of the physical environment in production quality.

The tool has yet to be rigorously evaluated by students, but initial positive feedback from teachers and students, allows us to consider its deployment in other courses and other levels of training.

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