Plackett-Burman designs

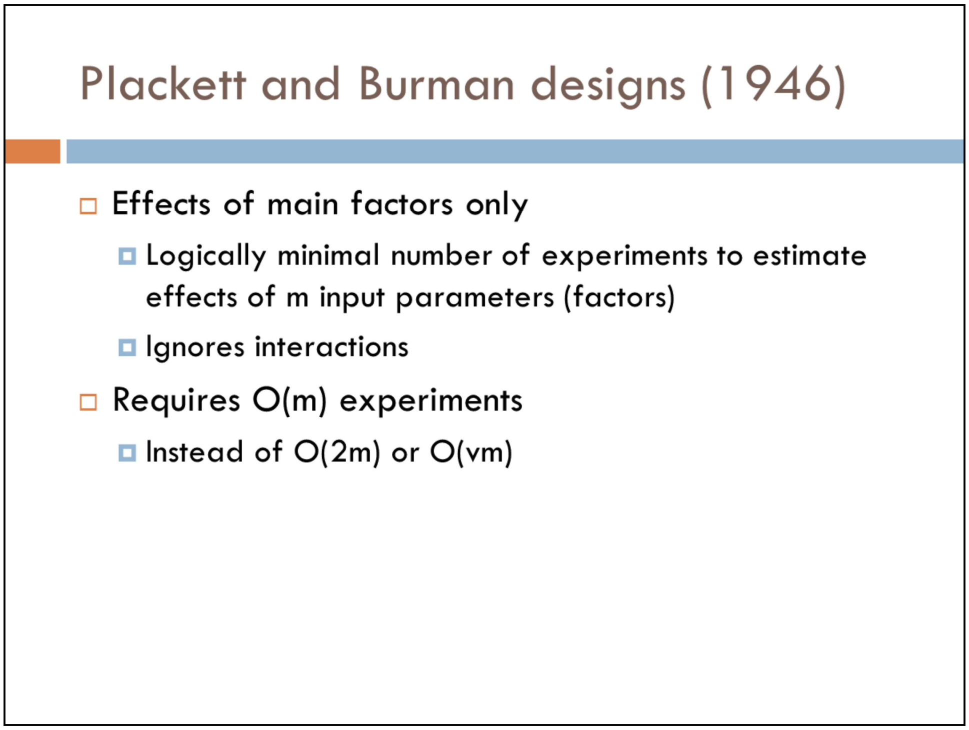
The Plackett-Burman designs is other alternative we have in order to reduce the number of scenarios to execute. It is widely used in the industrial area because, as we will see next is a fast approach to screen what happens in an environment with a huge number of factors.

Plackett-Burman designs

- In 1946, R.L. Plackett and J.P. Burman published their now famous paper "The Design of Optimal Multifactorial Experiments" in *Biometrika* (vol. 33). This paper described the construction of very economical designs with the run number a multiple of four (rather than a power of 2).
- Plackett-Burman designs are very efficient screening designs when only main effects are of interest.

The method is fully described on a paper of 1946, The Design of Optimal Multifactorial Experiments" in Biometrika (vol. 33). This paper described the construction of very economical designs, that means that the number of scenarios will be really small, compared with an alternative factorial design or a fractional factorial design. The first constrain that we found is that the number of scenarios will be a number a multiple of four (rather than a power of 2).

As you can imagine, the price we must pay for this reduction is huge, but, Plackett-Burman designs are very efficient screening designs when only main effects are of interest.



Plackett-Burman designs will analyze only main factors, no interactions, hence if you want to analyze the interactions of different factors of your model, this approach is useless. However, as we will see next, due to the high reduction in the number of scenarios to be considered, is reduced to O to m instead of O to 2 m or O to v m, the method is valid to do an initial screening, or if the main effects is the only element to consider for the analysis.

Plackett and Burman Designs

- PB designs exist only in sizes that are multiples of 4
- Requires X experiments for m parameters
  - X = next multiple of 4 $\geq$ m
- PB design matrix
  - Rows = configurations
  - Columns = factor's values in each configuration
    - High/low = +1/ -1
  - First row = from P&B paper
  - Subsequent rows = circular right shift of preceding row
  - Last row = all (-1)

How we will work with a Plackett and Burman Design?.

Well we will start understanding the design works only with multiples of 4 designs. This implies that the number of factors we will analyze cannot be any number, since we require X experiments for m parameters, hence X must be a multiple of 4, that will be bigger or equal to m.

In a Plackett and Burman design, as usual, the rows will represent the scenarios, or configurations, and the columns will be filled with the levels for the factors in each one of the different scenarios, represented as usual by minus or plus sign.

The novelty is that we will fill the table, the levels values, following a specific patters we see on the Plackett Burman design and shifting it one position.

The last row will be filled all with minus signs.

Plackett and Burman Designs

- PB designs also exist for 20-run, 24-run, and 28-run (and higher) designs.
- With a 20-run design you can run a screening experiment for up to 19 factors, up to 23 factors in a 24-run design, and up to 27 factors in a 28-run design.

Hence, with this consideration we can see that the Plackett Burman designs exists for 20-run, 24-run, and 28-run, and higher designs.

Notice also that with a 20-run design you can run a screening experiment for up to 19 factors, for 23 factors you can accommodate them in a 24-run design, and up to 27 factors in a 28-run design.

Notice also that you can always include in your analysis a factor that is not in your interest, only to accommodate the structure of the table, the constrain in the number of factors, to the Plackett and Burman design.

PB Design Matrix

Config	Input Parameters (factors)							Response
	A	B	C	D	E	F	G	
1	+1	+1	+1	-1	+1	-1	-1	
2	-1	+1	+1	+1	-1	+1	-1	
3	-1	-1	+1	+1	+1	-1	+1	
4	+1	-1	-1	+1	+1	+1	-1	
5	-1	+1	-1	-1	+1	+1	+1	
6	+1	-1	+1	-1	-1	+1	+1	
7	+1	+1	-1	+1	-1	-1	+1	
8	-1	-1	-1	-1	-1	-1	-1	
Effect								

Here you have a table for a Plackett and Burman design for a seven-factor analysis. Notice that we have here 8 different scenarios, that accomplish the restriction of be multiple of 4. The first row of the table follows the patters we can find on the paper, and from it, we shift the values of the levels one position, until the 8th row, where we will fill the levels with the minus sign.

PB Design Matrix

Config	Input Parameters (factors)							Response
	A	B	C	D	E	F	G	
1	+1	+1	+1	-1	+1	-1	-1	10
2	-1	+1	+1	+1	-1	+1	-1	12
3	-1	-1	+1	+1	+1	-1	+1	3
4	+1	-1	-1	+1	+1	+1	-1	5
5	-1	+1	-1	-1	+1	+1	+1	6
6	+1	-1	+1	-1	-1	+1	+1	5
7	+1	+1	-1	+1	-1	-1	+1	8
8	-1	-1	-1	-1	-1	-1	-1	9
Effect								

Now we are going to review how we can calculate the main effects for the design.

In the table are shown the results we obtain for each one of the different scenarios. Again, remember that those values are obtained from an analysis that assures that the number of replications in each scenario is enough.

PB Design Matrix

Config	Input Parameters (factors)							Response
	A	B	C	D	E	F	G	
1	+1	+1	+1	-1	+1	-1	-1	10
2	-1	+1	+1	+1	-1	+1	-1	12
3	-1	-1	+1	+1	+1	-1	+1	3
4	+1	-1	-1	+1	+1	+1	-1	5
5	+1	+1	-1	-1	+1	+1	+1	6
6	+1	-1	+1	-1	-1	+1	+1	5
7	+1	+1	-1	+1	-1	-1	+1	8
8	-1	-1	-1	-1	-1	-1	-1	9
Effect	-0,5							

$$-0.5 = (+1(10) + 1(5) + 1(5) + 1(8))/4 - (1(12) + 1(3) + 1(6) + 1(6))/4$$

From this, we can calculate the main effect for each factor. We can start with A, notice that the expression we will use take care of the sign of the level, and from it, we use the value in the positive part or the negative part of the expression. As an example, the 10 value will be located on the positive part, the 12, will be on the negative. With this we build our well-known expressions for the main factors.

PB Design Matrix

Config	Input Parameters (factors)							Response
	A	B	C	D	E	F	G	
1	+1	+1	+1	-1	+1	-1	-1	10
2	-1	+1	+1	+1	-1	+1	-1	12
3	-1	-1	+1	+1	+1	-1	+1	3
4	+1	-1	-1	+1	+1	+1	-1	5
5	-1	+1	-1	-1	+1	+1	+1	6
6	+1	-1	+1	-1	-1	+1	+1	5
7	+1	+1	-1	+1	-1	-1	+1	8
8	-1	-1	-1	-1	-1	-1	-1	9
Effect	-0,5	3,5	0,5	-0,5	-2,5	-0,5	-3,5	

Notice that the results we will obtain are those.

The sign in a Plackett Burman design is mealiness, this implies that we do not have information regarding if the effect is increasing or decreasing the answer variable. However we have information regarding the magnitude of the main effect.

PB Design

- Magnitude of effect is important, sign is meaningless.
- In the previous example (from most important to least important effects): B, G, E, A, C, D and F.

We summarize here the main important elements to consider in the analysis of the previous table.

Example

- A statistical approach to the experimental design of the sulfuric acid leaching of gold-copper ore.
- http://www.scielo.br/scielo.php?script=sci_arttext&pid=S0104-66322003000300010

Here you have an example of the application of the Plackett and Burman designs. Is an industrial process, and since the execution of the scenarios is expensive, the use of this approach is interesting, due to the huge reduction in the number of scenarios to be executed.

Our factors

Table 4: Mineralogical analysis of transition ore sample and sulfuric acid leach residue

Minerals	Molecular formulae	Assay (%)	
		Transition ore	Leach residue
Native Cu	Cu	0.39	0.30
Chalcopyrite	$CuFeS_2$	r	r
Bornite	Cu_5FeS_4	r	r
Chalcosite	Cu_2S	rr	rr
Covelite	CuS	rr	rr
Cuprite	Cu_2O	t	-
Malachite	$Cu_2(CO_3)(OH)_2$	t	-
Goethite/Limonite	$HFeO_2$ /$Fe_2O_3.H_2O$	26	21
Iron oxide	Fe_2O_3, Fe_3O_4	8	7
Clorite	$(Mg,Al,Fe)_{12}[(Si,Al)_8O_{20}](OH)_{16}$	33	35
Quartz	SiO_2	26	33

Notations -: not detected rr: very rare (some cristals) r: rare (~0.2%) t: trace (~0.5%) <1: ~0.8%

The factors we use in this example are materials that can be expensive, and, that we lose for each scenario, hence the reduction in the number of scenarios is crucial. Can you define a Plackett and Burman design for this example?

Please stop the video and try to do it by yourself.

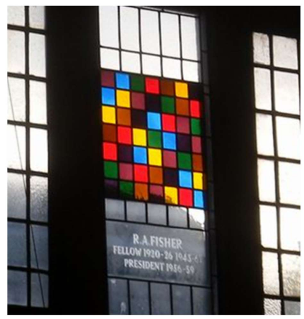
Table 5: Matrix for twelve replicated experiments based on the Plackett-Burman method and their respective copper extraction responses (R_1, R_2)

Test	Variable											Response (%)	
	A	X1	B	C	D	X2	E	F	G	X3	X4	R_1	R_2
1	+	+	-	+	+	+	-	-	-	+	-	70.5	71.8
2	+	-	+	+	+	-	-	-	+	-	+	77.6	77.4
3	-	+	+	+	-	-	-	+	-	+	+	67.2	68.2
4	+	+	+	-	-	-	+	-	+	+	-	73.2	74.4
5	+	+	-	-	-	+	-	+	+	-	+	77.0	76.8
6	+	-	-	-	+	-	+	+	-	+	+	76.5	77.9
7	-	-	-	+	-	+	+	-	+	+	+	74.0	73.5
8	-	-	+	-	+	+	-	+	+	+	-	59.9	59.9
9	-	+	-	+	+	-	+	+	+	-	-	73. 9	73.9
10	+	-	+	+	-	+	+	+	-	-	-	80.2	78.0
11	-	+	+	-	+	+	+	-	-	-	+	66.5	64.9
12	-	-	-	-	-	-	-	-	-	-	-	69.3	68.0

Here you have the result of the example. Notice that we follow the pattern of the paper?.

Latin squares

More than two levels.



Fisher window
Anders Sandberg

Other alternative to define an experimental design is the latin square, an alternative when the proposed methods presented until now does not accommodate in our analysis needs.

The term Latin square was first used by Euler in 1782.

The picture shows a 7 × 7 Latin square, the stained-glass window honors Ronald Fisher, whose book “Design of Experiments” discussed Latin squares. This is located on Caius College, Cambridge.

When to apply?

- Latin square designs are used when the factors of interest have more than two levels (k).
- We have tree factors.
- There are no (or only negligible) interactions between factors.

Latin square approach will be used when we have more than two levels for the different factors.

We constrain our analysis to three factors, and the interaction between the factors can be considered as negligible.

Pros and cons

- PROS:
  - They handle the case when we have several nuisance factors and we either cannot combine them into a single factor, or we wish to keep them separate.
  - They allow experiments with a relatively small number of runs.

- CONS:
  - The number of levels of each blocking variable must equal the number of levels of the treatment factor.
  - The Latin square model assumes that there are no interactions between the blocking variables or between the treatment variable and the blocking variable.

The advantages and the drawbacks of this approach is summarized here.

Example

- What is the best (fast) browser depending on the OS and the computer?
- Browsers are labeled by A,B, C and D.

	OS			
Computer	1	2	3	4
I3	A	B	C	D
I5	B	C	D	A
I7	C	D	A	B
XEON	D	A	B	C

Let’s go to review how we will work with Latin squares with an example.

Consider that you want to analyze what is the best browser, from the point of view of the speed needed to load a web page. To analyze this we want to consider the Operative System and the Hardware, the computer we use.

The browsers can be labeled from A to D.

With this considerations, one can build a table like the one presented on this slide. This table have one particularity, that is in each row or column, a single instance of each browser exists. This is a latin square.

Terminology

- A Latin Square is a **Standard Latin Square** when the letters of the first row and first column are arranged in alphabetical order (the previous example).
- Exists an unique standard 3×3 Latin Square, however there are four standard 4×4 Latin Square.

Square 1				Square 2				Square 3				Square 4			
A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
B	C	D	A	B	A	D	C	B	A	D	C	B	D	A	C
C	D	A	B	C	D	A	B	C	D	B	A	C	A	D	B
D	A	B	C	D	C	B	A	D	C	A	B	D	C	B	A

A standard latin square is a latin square where the letters of the first column are sorted in the alphabetical order. Notice that the semantics, what is the A browser does not affect this, since A will always represent the same browser.

We know that depending on the dimension of the lain square, one can define different number of standard latin squares, for a dimension of 3 x 3 latin square there is only one, but for a 4 x 4 lain square exists 4 different standard latin square.

Creating a Latin Square design

- Write down any Latin square of the required size (it could be a standard Latin square).
- And randomize:
  - Randomize the order of the rows.
  - Randomize the order of the columns.
  - Randomize the allocation of treatments to the letters of the square.

To work with Latin square approach, first we will determine the dimension of the latin square, that depends on the number of levels we want to consider for our object of the analysis.

Then we will write the Latin square of the required size, it can be a standard latin square.

And form this we do the randomization. This is a key aspect that we do not forgot.

First, we randomize the order of the rows. Next, we randomize the order of the columns, and finally we randomize the allocation of treatments to the letters of the square.

The model

- $Y_{ijt}=\mu+R_i+C_j+T_k+\varepsilon_{ijk}$
- Where
- Y_{ijt} denoting any observation for which
  - $X_1 = i, X_2 = j, X_3 = k$
  - X_1 and X_2 are blocking factors
  - X_3 is the primary factor (treatment).
- μ denoting the general location parameter
- R_i denoting the effect for block "i"
- C_j denoting the effect for block "j"
- T_k denoting the effect for treatment "k"

The statistical model we use to calculate the Latin Square is presented on this slide.

Y is denoting any observation where Z are the blocking factors and X 3 is the treatment, the primary factor we analyze.

μ is denoting the general location parameter.

R_i is denoting the effect for block "i".

C_j is denoting the effect for block "j".

T_k is denoting the effect for treatment "k".

With this we will be able to calculate an ANOVA model where we analyze the differences between the different groups, we define thought the levels of each factor.

Calculating the model

- Estimate for μ: $\bar{Y}$ = the average of all the data
- Estimate for Ri: $\bar{Y_i} - \bar{Y}$
  - $\bar{Y_i}$ = average of all Y for which X1 = i
- Estimate for Cj: $\bar{Y_j} - \bar{Y}$
  - $\bar{Y_j}$ = average of all Y for which X2 = j
- Estimate for Tk: $\bar{Y_k} - \bar{Y}$
  - $\bar{Y_k}$ = average of all Y for which X3 = k
- Estimate for ε_{ijk}
  - $\varepsilon_{ijk} = (y_{ijk} - \bar{y}_i - \bar{y}_j - \bar{y}_k + 2\bar{y})$

To do so we estimate the different parameters we need for the model. In this slide is presented how we will do this estimation, mainly calculating the means for each subgroup.

The ANOVA table

Source	SS	df (N-1)=k²-1	MS	F
Row	SSROW	k-1	MSROW =SSROW /df	MSROW/MSE
Column	SSCOL	k-1	MSCOL =SSCOL/df	MSCOL/MSE
Treatments	SSTR	k-1	MSTR =SSTR/df	MSTR/MSE
Error	SSE	(k-1)(k-2)	MSE =SEE/df	

$$\underbrace{\sum_{j=1}^{k}\sum_{i=1}^{k}(y_{ijt}-\bar{y})^2}_{\text{TSS}} = \underbrace{k\sum_{i=1}^{k}(\bar{y}_{i..}-\bar{y})^2}_{\text{SSROW}} + \underbrace{k\sum_{j=1}^{k}(\bar{y}_{.j.}-\bar{y})^2}_{\text{SSCOL}} + \underbrace{k\sum_{t=1}^{k}(\bar{y}_{.t.}-\bar{y})^2}_{\text{SSTR}} +$$

$$+\underbrace{\sum_{i=1}^{k}\sum_{j=1}^{k}\sum_{t=1}^{k}(y_{ijt}-\bar{y}_{i..}-\bar{y}_{.j.}-\bar{y}_{..t}+2\bar{y})^2}_{\text{SSE}}$$

Then we can compose the ANOVA table as is shown here. Then we can calculate for each factor, represented on the Row, Column and Treatments if the p.value, from the F distribution, shows that there is an effect for each one of them.

Example

- A courier company is interested in deciding between five brands (D,P,F,C and R) of car for its next purchase of fleet cars.
  - The brands are all comparable in purchase price.
  - The company wants to carry out a study that will enable them to compare the brands with respect to operating costs.
  - For this purpose they select five drivers (Rows).
  - In addition the study will be carried out over a five-week period (Columns = weeks).

Lets' go to review a well-known example to illustrate the Latin Square approach. Think that we have a courier company that wants to buy a new fleet of cars. They can choose between 5 different brans, that we will name D,P,F,C and R.

We assume that the price is not an element to be considered on the analysis, they have more or lees the same price, hence we will be focused on the operating cost depending on the brands.

To do so we select 5 set of drivers, that we consider equivalent, and as the needed additional factor, we chose a 5-week period, also considered equivalent.

Example

- Each week a driver is assigned to a car using randomization and a Latin Square Design.
- The average cost per mile is recorded at the end of each week and is tabulated below:

		Week				
		1	2	3	4	5
Drivers	1	5.83	6.22	7.67	9.43	6.57
		D	P	F	C	R
	2	4.80	7.56	10.34	5.82	9.86
		P	D	C	R	F
	3	7.43	11.29	7.01	10.48	9.27
		F	C	R	D	P
	4	6.60	9.54	11.11	10.84	15.05
		R	F	D	P	C
	5	11.24	6.34	11.30	12.58	16.04
		C	R	P	F	D

From this we define a Latin square analysis, assigning each week a driver to a car.

Remember that previous to do this assignation we do the needed randomization process, the randomization of the order of the rows, the drivers, the randomization of the order of the columns, the weeks, and finally the randomization of the allocation of treatments to the letters of the square, in that case the brands.

With this we execute the different scenarios and we obtain the solutions we shown here.

Example

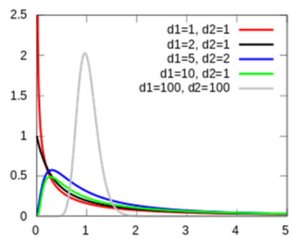
- The Anova Table for Example

Source	S.S.	d.f.	M.S.	F ratio	F (table α=0.05%)
Week	51.17887	4	12.79472	16.06	F(4,12)=3.25
Driver	69.44663	4	17.36166	21.79	
Car	70.90402	4	17.72601	22.24	
Error	9.56315	12	0.79693		
Total	201.09267	24			

Adding the values to the table, and calculating the results, we obtain this solution. The F from the table for the week factor provides a value of 3.25, see the next slide. It seems that we are in the rejection area, hence there is an effect for weeks. Can you do the same for Driver and Car?

F-table

	Numerator df: df_B				
df_W	1	2	3	4	5
5 5%	6.61	5.79	5.41	5.19	5.05
1%	16.3	13.3	12.1	11.4	11.0
10 5%	4.96	4.10	3.71	3.48	3.33
1%	10.0	7.56	6.55	5.99	5.64
12 5%	4.75	3.89	3.49	3.26	3.11
1%	9.33	6.94	5.95	5.41	5.06
14 5%	4.60	3.74	3.34	3.11	2.96
1%	8.86	6.51	5.56	5.04	4.70

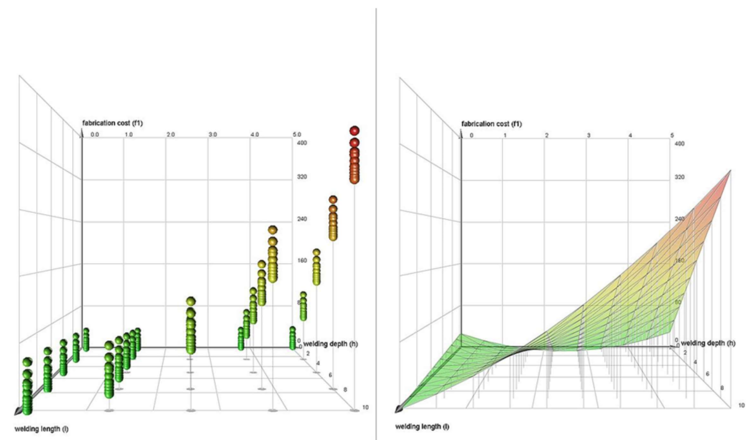


This is the well-known table for the F distribution. In or case we have 4 and 12 degrees of freedom, resulting in a critical value of 3.26 working at 5%.

Response surface methods

At this point we see several methods to analyze a set of scenarios. These scenarios represents a space that will be explored by a mechanism, in that case a simulation model, that uses the levels of the different factors to explore the landscape.

From full factorial design to the surface



By Robiminer - Own work, CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=18558398

Graphically the exploration of the space, can be represented as is on this picture. On the right side is presented the space that depicts the exploration area, on the left side is presented a full factorial design, where several points are analyzed, the scenarios represented by the levels.

Notice that at this point one can suggest to use a method to explore a subset of the space, in this case, this subset can be selected using an optimization algorithm, or a heuristic algorithm. In the case of the heuristic named Hill-Climbing, one will define a method to “go up” trough the mountain that we find when we execute the scenarios, and thanks to this, reduce the number of scenarios to execute. In this case we are focused in finding the best, higher scenario, and not in the analysis of main effects and interactions.

Steps

1. Set objectives
2. Select process variables
3. Select an experimental design
4. Execute the design
5. Check that the data are consistent with the experimental assumptions
6. Analyze and interpret the results
7. Use/present the results (may lead to further runs or DOE's).

Finally, here are depicted the main steeps to perform a Design of Experiments.

First, we set objectives.

Second is needed to select process variables to be used on the analysis.

Third we will select an experimental design according to the constrains we have.

Then we will execute the design, and the different scenarios, assuring that we conduct the replications correctly, and that all the assumption for the Experimental Design are meet.

Once done the execution we will check that the data are consistent with the experimental assumptions, and perform the validations needed.

If all seems correct, then we can go further and analyze and interpret the results.

Finally, we will use and present the results, this may lead to further runs or other Experiments to be conducted.

Planning and running DOE

- Check performance of gauges/measurement devices first.
- Keep the experiment as simple as possible.
- Check that all planned runs are feasible.
- Watch out for process drifts and shifts during the run.
- Avoid unplanned changes (e.g., swap operators at halfway point).
- Allow some time (and back-up material) for unexpected events.
- Obtain buy-in from all parties involved.
- Maintain effective ownership of each step in the experimental plan.
- Preserve all the raw data--do not keep only summary averages!
- Record everything that happens.
- Reset equipment to its original state after the experiment.

To finish, here you have some interesting recommendations regarding on how to plan and run an Experimental Design.

Check performance of gauges and measurement devices first. We must assure that the information that we are going to use comes from devices that are working well enough for our purposes.

We must keep the experiment as simple as possible; it is not needed to include artifacts that makes the experiment complex and difficult to understand.

Check that all planned runs are feasible, if there are some scenario that is unrealistic, the Experimental Design will fail.

Watch out for process drifts and shifts during the run.

Avoid unplanned changes, as an example, swap operators at halfway point. This makes that you lose a lot of time.

Allow some time, and back-up material, for unexpected events.

Obtain buy-in from all parties involved. As we will see on Validation section, this also increases the confidence of the parties involved on the results.

Maintain effective ownership of each step in the experimental plan. If not, the experiment can fail because the direction of the analysis, the goals. changes.

Preserve all the raw data, do not keep only summary averages, to be able to reproduce all the experiment again.

Record everything that happens, this is enforced by law in some scenarios.

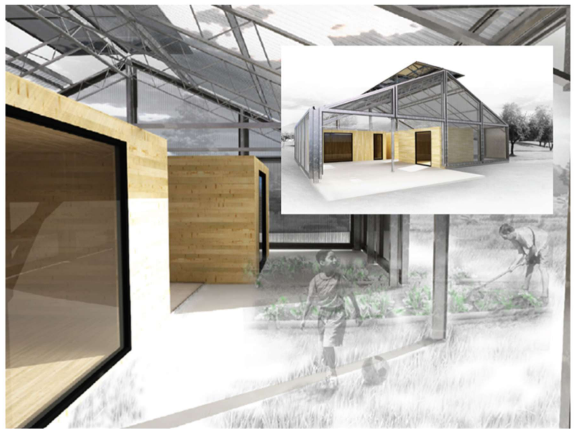
Reset equipment to its original state after the experiment. We want that wen we are going to start an experiment if the material we are using is shared by a community, think the university, it is clean and ready to use.

Case study

DOE applied to construction problems

Here we are presenting a case study based on a real project. In this case study we use an intensive experimental design. This is just an introduction to the case, below you will find some papers where more technical information can be consulted.

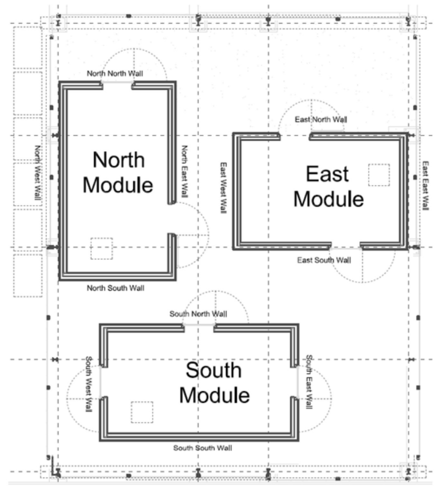
Solar Decathlon Europe, LOW3



The case we are presenting is a real case that happens during the Solar Decathlon Europe competition. The Solar Decathlon Europe was initiated in 2007. It is an international competition that challenges collegiate teams to design and build houses powered exclusively by the sun.

The 2010 UPC solar decathlon building, the Low 3 is presented on this pictures.

Solar Decathlon Europe, LOW3



The building has been composed by 3 modules, the North, the East and the South module, all that are inside a greenhouse that helps to keep the temperature all homogeneous. One of the main concerns of the building is what will be the materials to use in each one of the different modules, and what will be the best orientation in order to minimize the energy consumption.

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	North MODULE				South MODULE				East MODULE			
U (W/m2 K)	North Wall	West Wall	South Wall	East Wall	North Wall	West Wall	South Wall	East Wall	North Wall	West Wall	South Wall	East Wall
s1	0,212	0,212	0,212	0,212	0,212	0,212	0,212	0,212	0,212	0,212	0,212	0,212
s2	0,212	0,212	0,212	0,212	0,212	0,212	0,212	0,212	0,212	0,212	0,212	0,174
s3	0,212	0,212	0,212	0,212	0,212	0,212	0,212	0,212	0,212	0,212	0,174	0,212
s4	0,212	0,212	0,212	0,212	0,212	0,212	0,212	0,212	0,212	0,174	0,212	0,212
...	...	...	...	...	...	...	...	...	...	...	...	...
S4096	0,174	0,174	0,174	0,174	0,174	0,174	0,174	0,174	0,174	0,174	0,174	0,174

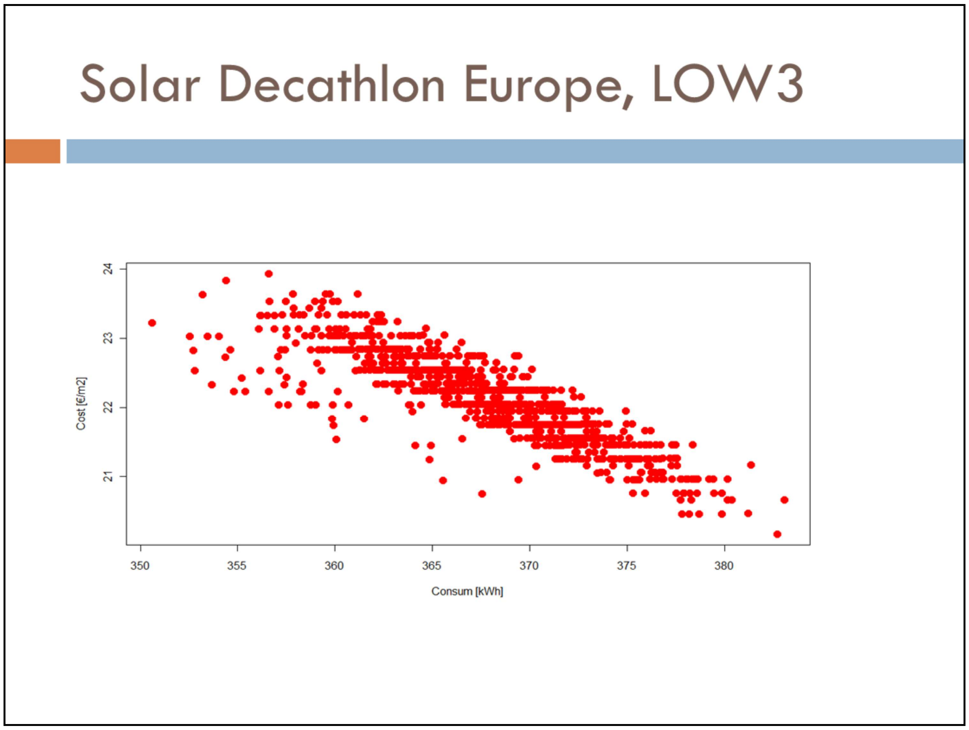
	North MODULE				South MODULE				East MODULE				Results
U (W/m2°K)	North Wall	West Wall	South Wall	East Wall	North Wall	West Wall	South Wall	East Wall	North Wall	West Wall	South Wall	East Wall	KWh
1	0	0	0	0	0	0	0	0	0	0	0	0	386,99
2	0	0	0	0	0	0	0	0	0	0	0	1	383,30
3	0	0	0	0	0	0	0	0	0	0	1	0	383,71
4	0	0	0	0	0	0	0	0	0	0	1	1	378,86
5	0	0	0	0	0	0	0	0	0	1	0	0	381,82
6	0	0	0	0	0	0	0	0	0	1	0	1	380,42
7	0	0	0	0	0	0	0	0	0	1	1	0	379,96
8	0	0	0	0	0	0	0	0	0	1	1	1	375,42

To do so, we develop a simulation model that expresses the energy consumption of this building, using in this case a simulation engine named NECADA, see https://necada.com.

With this, we will able to define an experimental design, as you can see here, a full factorial design. On the upper table is presented just a subset of the 4096 different scenarios to consider, you can see the values, levels, for the different factors we consider. This levels represents the materials we will use on the building construction.

On the table below is shown the results for the first 8 different scenarios.

In this case of problem some different difficulties exists, like that to execute a single replication of a scenario it is needed about 15 minutes to obtain the answer.



Although the time needed to execute all the experiment is high, the experiment was conducted in a distributed environment, in a cluster of computers, that allows to obtain the answers in a proper time. Here is presented the results, the different buildings scenarios depending on the two factors we want optimize, the Cost and the energy consumption. The values that are located on the lowest area of the cloud, that forms a frontier of what is named, non-dominated solutions, are the solutions of our interest.

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- Using Yates

Module	Wall	Effects	Mean
East	East Wall	4,35	3,34
	South Wall	3,09	
	West Wall	3,26	
	North Wall	2,66	
South	East Wall	2,23	2,54
	South Wall	2,16	
	West Wall	3,44	
	North Wall	2,35	
North	East Wall	2,74	3,46
	South Wall	4,65	
	West Wall	1,60	
	North Wall	4,86	

WE apply a Yates algorithm to understand main effects and interactions and we obtain a big table that we summarize on the table presented on this slide. As one can see, the north module is the one that have more effect on energy consumption, hence it is important to isolate well first this module, then the East module, and finally the South module. Notice also that we have the detail for each one of the different walls of the different modules, if we prefer to use different material, not for module, but for each one of the walls.

Solar Decathlon Europe, LOW3

- To know more:
  - Fonseca i Casas, P., Fonseca i Casas, A., Garrido-Soriano, N., & Casanovas, J. (2014). Formal simulation model to optimize building sustainability. *Advances in Engineering Software*, *69*, 62–74. doi:10.1016/j.advengsoft.2013.12.009

To know more you can consult this paper or access the bloc of the project necada at https://news.necada.com