

## THE GARDEN SPRINKLER: AN INTERACTIVE WEB-BASED APPLICATION FOR TEACHING DESIGN OF EXPERIMENTS

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*Most exercises for teaching students Response Surface Methodology deal with setting up the experiment itself or analyzing the data after the fact. As such, the experience of “learning-by-doing” and drawing intermediate conclusions is lost. For this reason a web-based application was developed, based on a real-life problem dealing with the multi-objective optimization of a garden sprinkler having 8 design parameters and 3 responses. Participants interact with the tool to get the response data for their own designs. Depending on the choice of the considered response(s), different design parameters are active and should be analyzed. By inserting a design into the application, the corresponding responses are generated and can be used for analysis and follow-up experimentation. The tool has been successfully used both in company training and academic courses.*

### INTRODUCTION

The response surface methodology (RSM) is an interplay between the design of the experiments (DOE) and the analysis thereof, during which the experimenter has to make decisions and considerations at multiple stages, for example:

- Which design to use for screening and optimization?
- What about replication, randomization and blocking?
- How to handle multi-response optimization?
- Which regression method to use?
- How to choose the active factors?
- How to set inactive factors in the process?
- ...

When teaching RSM, exercises covering those aspects are essential and can be performed at different levels. Classically, textbook exercises that cover a specific part are given – regression exercises including the issue of subset selection, designing the experiment itself, analyzing multiple responses, and so on. Although those exercises are of great use, they lack the intermediate conclusions to be drawn and, based on those, to choose the ideal follow-up experimentation. At the other side, easy-to-perform real-life experiments were developed to teach DOE and RSM, such as Box’s paper helicopter (Box, 1992) and the catapult (Antony, 2002). Such approaches challenge the students in every step of the experiment so that they go through the whole process they would encounter in real-life. The drawback, however is the fact that experimenting takes time and space which is not always sufficiently available.

In between those options, virtual experiments do offer the advantage of covering the whole process of experimenting, analyzing and making (interim) conclusions as well as the fact that besides a computer and software no additional material is required and results are available instantaneously. A library of such virtual experiments, which was originally called “VIRTEX” but which was later renamed “env2exp” (<http://lstat.kuleuven.be/env2exp/DOE/index.html>), was developed by Darius et al. (2003) and was extensively used for training purposes.

The goal of this contribution was to develop a new virtual experiment where a multi-input multi-output (MIMO) process needs to be optimized: several variables potentially influence the output quality, and this overall output quality is defined by multiple quality characteristics. Statistical concepts that are handled in the experiment are:

- DOE: from screening towards second order designs
- Multiple response optimization (e.g. Derringer Desirabilities)

- Possibility to remove noise and so to use the exercise for teaching Design and Analysis of Computer Experiments (DACE)
- Blocking
- ...

**THE GARDEN SPRINKLER**

The basis for the virtual experiment is a physics-based simulation model of a garden sprinkler, taken from Siebertz et al. (2010). In order to optimize the performance of such a sprinkler one can adapt eight different input parameters (angles, lengths, moments of friction, diameters, pressure – Figure 1). The performance consists of three different aspects – the range covered by the sprinkler and the rotation speed (both to be maximized) and the water consumption (to be minimized). A graphical representation of the garden sprinkler and its parameters is given in Figure 1.

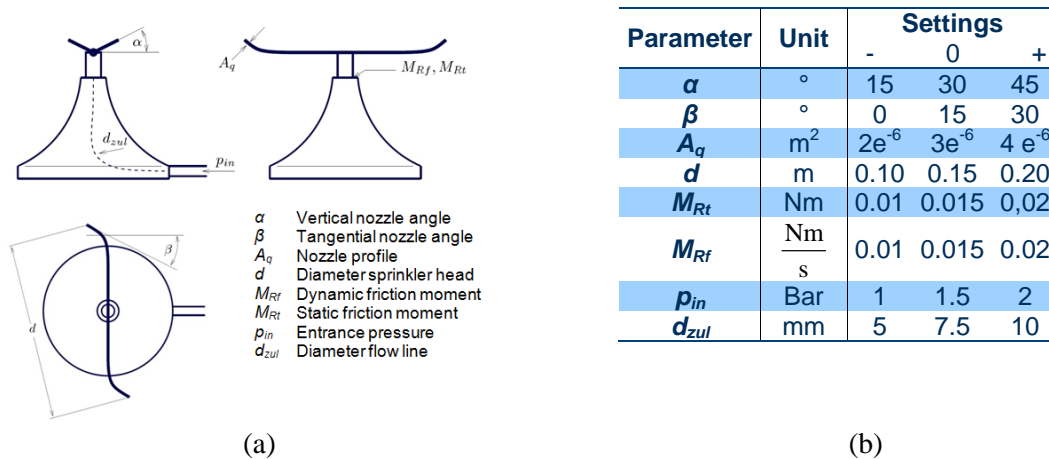


Figure 1: A schematic representation of the garden sprinkler with a description of the eight different settings that can be adapted (taken from Siebertz et al., 2010) (a) and the limits of those settings (b).

**THE SIMULATOR**

The simulator can be found at [www.experimental-design.eu/sprinkler](http://www.experimental-design.eu/sprinkler) and has three main windows. In the Global configuration window (Figure 2a) there are four different settings one can choose:

- Control whether the experiment should be run with measurement noise (i.e. mimicking the real, physical experiment) or without (so to use the simulator for a course in DACE);
- Control whether a blocking variable should be included, for instance to mimic the situation where part of the sprinklers were produced during day 1 and the remaining during day 2;
- Control which response(s) to consider. The inclusion of multiple responses makes the simulator particularly interesting when teaching multiple response optimization (e.g. with Derringer Desirability functions);
- Control the decimal separator (comma or point).

In the second window, the Design Configurator, the experimenter has to choose which of the eight input variables are considered in the simulator runs. For instance in a screening design, which would be the natural choice to start the optimization exercise with, all eight input variables will typically be considered. If, after running this design and analyzing the results, only some of them show up to be significant, the experimenter has to make a choice at which level to fix the non-active factors (f.i. the cheapest value, or the one with the highest response).

Finally, in the third window the design, which can be generated in any statistical software, needs to be inputted. This can be done by simply uploading the file as a tab delimited ascii file, or with a copy-paste operation from f.i. JMP. Once the design is uploaded or inserted, pressing the Calculate button will perform the underlying simulations and a tab delimited file is generated

within seconds in which the response(s) are generated for all the experimental settings that were invoked. This file can then be used in any software to analyze.

Alpha [°]  In design  Low limit (15)  Midpoint (30)  High limit (45)  
 Beta [°]  In design  Low limit (0)  Midpoint (15)  High limit (30)  
 Aq [m<sup>2</sup>]  In design  Low limit (2E-06)  Midpoint (3E-06)  High limit (4E-06)  
 d [m]  In design  Low limit (0.1)  Midpoint (0.15)  High limit (0.2)  
 mt [Nm]  In design  Low limit (0.01)  Midpoint (0.015)  High limit (0.02)  
 mf [Nm/s]  In design  Low limit (0.01)  Midpoint (0.015)  High limit (0.02)  
 pin [Bar]  In design  Low limit (1)  Midpoint (1.5)  High limit (2)  
 dzul [mm]  In design  Low limit (5)  Midpoint (7.5)  High limit (10)

(a)

**Input data**

Please input data uploading a design file (explanation of the correct format for the design file can be found [here](#), software to generate the design doesn't matter as long as these rules are followed while saving it).

**Upload a design**

Geen bestand gekozen

**Paste data from JMP**

45	30	0.000004	0.1	0.01	0.01	1
45	0	0.000004	0.1	0.02	0.01	2
45	0	0.000002	0.2	0.02	0.01	1
15	30	0.000002	0.1	0.02	0.01	2
45	30	0.000002	0.2	0.01	0.01	2
45	30	0.000002	0.1	0.02	0.02	1
15	0	0.000002	0.2	0.02	0.02	2
15	30	0.000004	0.1	0.01	0.02	2
15	30	0.000004	0.2	0.02	0.01	1

(b)

Figure 2: The Design Configuration tab (a) and the options for inserting the design into the simulator (b).

**EXAMPLE**

As an example, suppose we are interested in maximizing the range and minimizing consumption, but do not consider the speed. This is done by selecting those two responses in the Global configuration window. Below we briefly summarize some of the typical steps that would be needed to optimize those two responses.

*Screening step:* A screening step is used to pinpoint active factors. Suppose now we identified during a screening step that the pressure, the nozzle angle and nozzle profile are the factors that are significantly affecting the range and/or consumption so that we would like to investigate their influence in more detail in a next step.

*Limited response surface:* We are now focusing on the three active factors and search for the settings at which a desirable sprinkler is obtained. This could for instance be done using a limited response surface design (e.g. a full factorial design with some center points). The first step to perform then is to tell the simulator that only three input variables will be considered, and to fix the other five inputs. This is done in the Design Configurator as shown in Figure 3. Next, the full factorial design with only the three active input variables is generated in any software, and the design is uploaded or pasted in the appropriate data window of the simulator, after which a results file is created. This file can then be imported in any statistical software for analysis (e.g. main effects and interactions model, eventually complemented by a Lack-of-fit test).

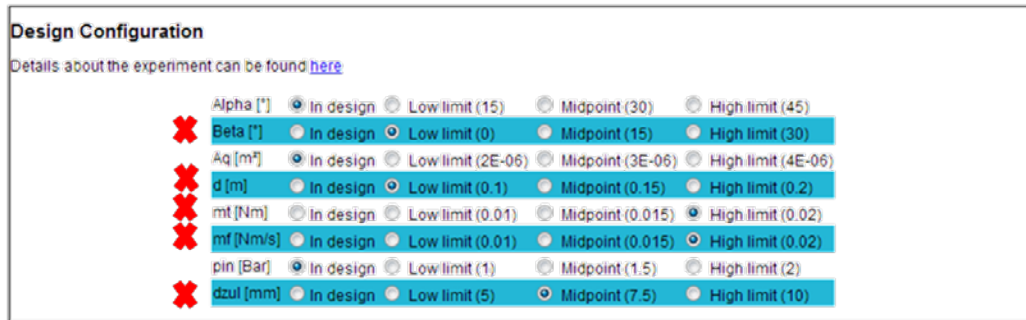


Figure 3: The Design Configuration tab where the simulator is told that only three input variables will be used in the design.

*Full response surface:* The underlying model is nonlinear in nature. Suppose that the previous step resulted in a significant Lack-of-fit test so that additional experimenting is required, e.g. using a central composite design. A possible visualization of the garden sprinkler solution is then presented in Figure 4. The influence of the *Alpha*, *Aq* and *pin* on both responses is shown, as well as the desirability functions.

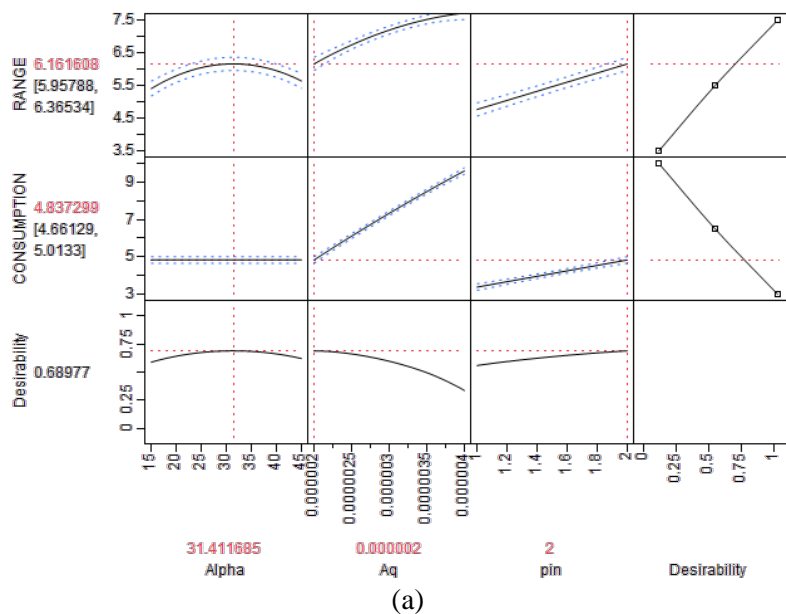


Figure 4: An example model of the garden sprinkler showing the influence of *Alpha*, *Aq* and *pin* on the range and consumption.

CONCLUSION

An easy-to-understand web-based simulator was created for teaching design of experiments. Being versatile, it offers the possibility to cover a very broad range of topics and is independent from the statistical software that is used.

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