Analysis of Agricultural and Engineering Systems using Simulation Decomposition

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Abstract. This paper focuses on the analysis of agricultural and engineering processes using simulation decomposition (SD). SD is a technique that utilizes Monte Carlo simulations and distribution decomposition to visually evaluate the source and the outcome of different portions of data. Here, SD is applied to three distinct processes: a model problem, a non-destructive evaluation testing system, and an agricultural food-water-energy system. The results demonstrate successful implementations of SD for the different systems, and the illustrate the potential of SD to support new understanding of cause and effect relationships in complex systems.

Keywords: Simulation decomposition · food-water-energy systems · non-destructive evaluation · physics-based simulations · parameter variability.

1 Introduction

Simulation decomposition (SD) [1] is not only a great visualizing technique for engineering processes, but also an efficient application to utilize the resulting data set created by the Monte Carlo [2] sampling process. An illustration, such as a stacked bar chart, can express the decomposed variability of simulation inputs and outputs to understand the results. Furthermore, SD has the potential to understand cause and effect relationships between the input and output parameters of a given system [3].

In this work, a recent SD method [3] is applied to problems in the area of agriculture and engineering system analysis. The first problem is intended

to illustrate the SD method using is a model problem with three inputs and one output. The second problem has relevance to nondestructive evaluation and involves an ultrasonic testing (UT) system with a pillbox void. The last problem involves an agricultural model that computes the nitrogen export of the state of Iowa. The commonality of the second and the third problems is that they both involve processes that utilize physics-based computational simulations and have input parameters with variability. The SD analysis provides a graphical representation of the effect of input variability on the simulation outputs.

The next section gives the formulation of the problem and a description of the SD analysis technique. The following section presents the results of the three numerical cases. The last section summarizes this work and discusses the potential future work.

2   Methods

This section describes the general problem formulation and gives the details of the SD method.

2.1   Problem statement

System analysis can be represented as a black box model as

$$y = f(\mathbf{x}), \tag{1}$$

where the left-side of the equation represents the model output y and the right-side of the equation represents the model f with input parameters $\mathbf{x}$. It is important to understand the effects of uncertainties of the input parameters on the output response when making design decisions. In this work, the effects of the input parameters on the output parameters are visualized using simulation decomposition (SD).

2.2   Simulation decomposition

SD [1, 3] is an approach to visualize the effects of variability on models. Furthermore, SD analysis is used to distinguish the influences of different cases of inputs affecting the model output. Figure 1 shows a flowchart of the SD workflow. The process starts by generating random samples as the input data set. First, specify the statistical distributions for each input parameter and choose the states of interest for each input parameter individually. Then, divide the distributions into sub-distributions according to the chosen states. Next, generate every possible combination of the input data from the sub-distribution using Monte Carlo sampling and categorize them into different cases. These cases would determine the model output that is to-be-decomposed. Then, conduct the simulations with the input samples and obtain the output data set. Meanwhile, register the output of each simulation according to their cases. Lastly, construct the outcome probability for each case and decompose the full outcome probability into different cases
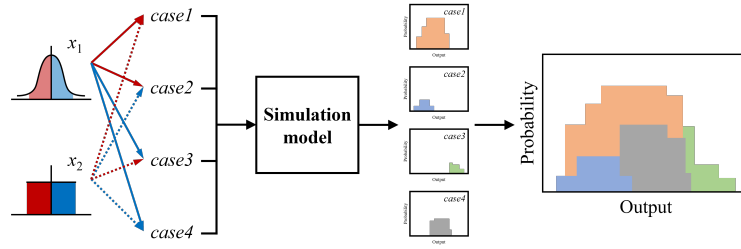
Fig. 1: A schematic of the simulation decomposition workflow.

accordingly. The importance of each case can be observed by the occurrence in the decomposed output visually, and cross-checking important cases provide a sense of importance for the input parameters.

3 Numerical Examples

This section presents the results of SD analysis of a model problem, an ultrasonic nondestructive testing system, and the Iowa food-energy-water system analyzed.

3.1 Model problem

The simple analytical function is written as [4]

$$y(\boldsymbol{x}) = x_1 + x_2 x_3^2, \tag{2}$$

where x_1, x_2, and x_3 are the input parameters with the variabilities given in Table 1, and y is the function output parameter. A data set of a total 10^6 points is created using Latin hypercube sampling (LHS) [5].

Figure 2 shows how each input parameter is decomposed into two states that define eight cases for the parameter space. All the parameters are considered to be uniformly distributed. For x_1, 500 is set to divide the complete distribution into sub-distribution, and 50 and 5 are used to divide x_2 and x_3, respectively.

Figure 3 shows the decomposed distribution of the output y. In general, a low value of y is contributed by almost all combinations of the input parameters.

Table 1: Input parameters and their statistical distributions for the model problem.

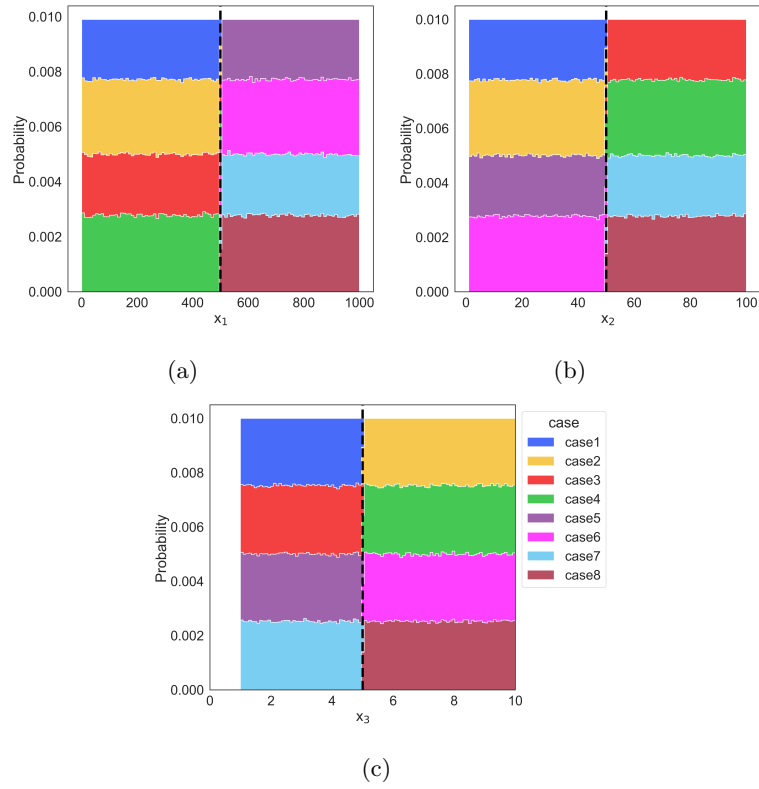| Parameter	Distribution
x_1	$U(1, 1000)$
x_2	$U(1, 100)$
x_3	$U(1, 10)$

(a)

(b)

(c)

Fig. 2: Decomposed distribution of input parameters from SD for the model problem.
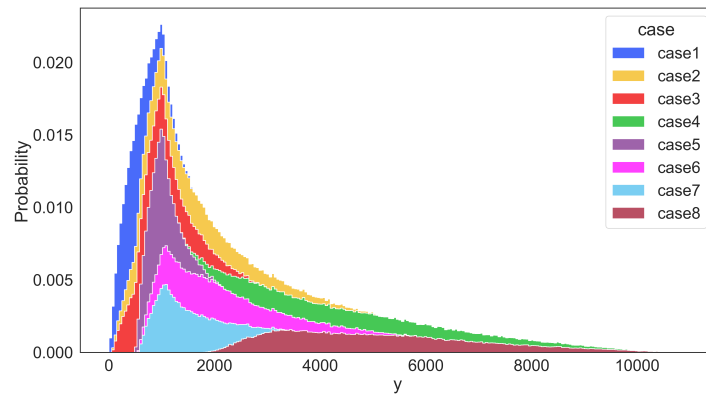

Fig. 3: Decomposed distribution of the model problem output.

However, a high value of y is mainly obtained by the cases with high values of x_2 and x_3. In particular, in the cases where x_1 and x_2 are both low, the simple function can still yield high y with high x_3, and vice versa. In this case, the SD analysis shows that the output of the analytical function is dominated by x_3, which is as expected when inspecting the function directly.

3.2   Ultrasonic testing (UT) system with a pillbox void

Ultrasound testing (UT) is a widely used nondestructive testing (NDT) technique for flaw detection. In this problem, a pillbox-inclusion-defect under planar UT transducer is considered [6]. Figure 4 shows the setup of the problem. The planar transducer is placed in water and the probe angle (θ) and the probe co-ordinates (x and y) are varied. A fused quartz block with a pillbox-like void is inspected by the transducer where the distance between the transducer and the surface of the block (z_1) and the distance between the surface of the block and the defect (z_2) can vary based on the setup. The variability distributions for this problem are given in Table 2. The output response is the reflected pulse (v) received by the transducer. A data set of 10^5 data points is generated by LHS [5] for this problem.

Figure 5 shows the sub-distributions of sampled input parameters in two states. The variability of probe angle (θ) is considered normal distribution and the rest of input parameters are considered uniform distributions in this problem. For θ, the complete distribution is divided by the statistical mean of 0 degree. The sub-distributions of the probe coordinates x and y are both divided by 0.5 mm. z_1 and z_2 are consider using full distribution in this work for simplicity. The total of eight cases are shown in figure 5.

Figure 6 shows the decomposed distribution of output response (v). A diagonal trend can be observed. In particular, the SD analysis shows that high values of the inputs yield low values of response. Furthemore, the results show that the response is dominated by θ, followed by x, and then y.
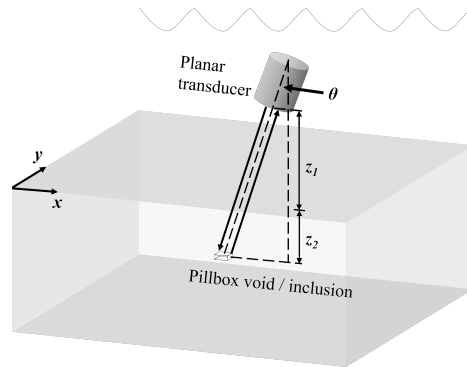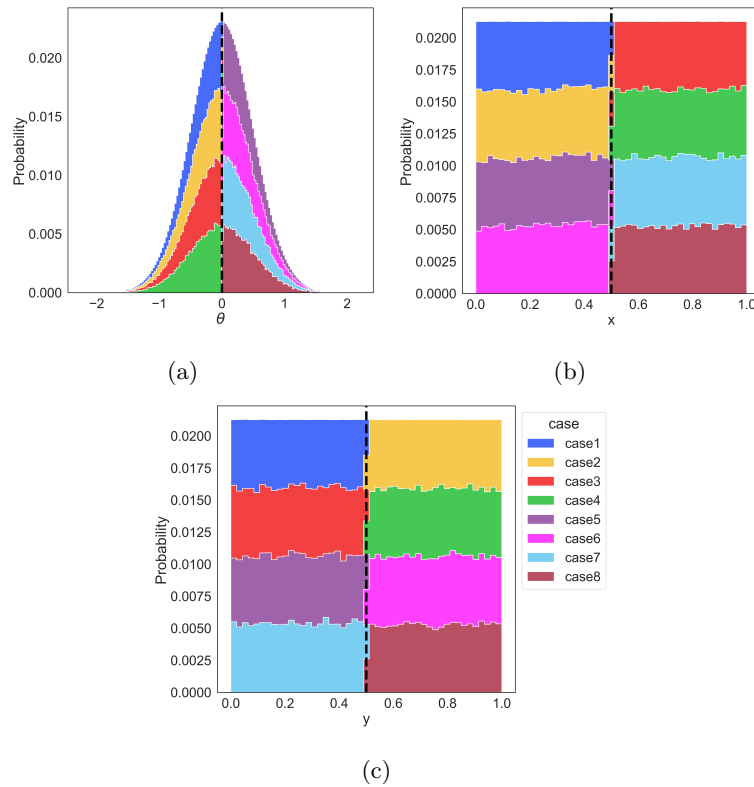

Fig. 4: A schematic showing the setup of the ultrasonic testing system.

Table 2: Ultrasonic testing system input parameters statistical distributions.

Parameter	Distribution
θ (deg)	$N(0,\ 0.5^2)$
x (mm)	$U(0,\ 1)$
y (mm)	$U(0,\ 1)$
z_1 (mm)	$U(24.9,\ 25.9)$
z_2 (mm)	$U(12.5,\ 13.5)$

(a)

(b)

(c)

Fig. 5: Decomposed distribution of input parameters from SD for UT system.

3.3   Iowa food-energy-water system

A simulation-based model of the Iowa food-water-energy (IFEW) system computes the surplus nitrogen (N_s) considering the weather, agriculture, and animal agriculture domains in the state of Iowa [7]. Figure 7 show an extended design structure matrix (XDSM) diagram of the simulation model. The input parame-
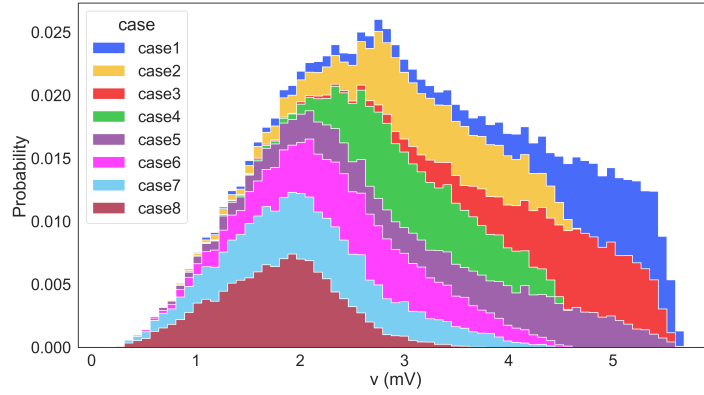
Fig. 6: Decomposed distribution of ultrasonic testing system output parameter.

ters, intermediate parameters and output parameters are listed in Table 3, and the details of the computation for different domains are described in [7]. This work focuses on the SD analysis of the variability input parameters given in Table 4 and assumes other input parameters are fixed. A data set of 10^5 points is created for the SD analysis using LHS [5].

Figure 8 shows the distribution of sampled input parameters in two states and the four corresponding cases. The variability distributions of the July temperature (w_1) and precipitation (w_2) are considered to be normal and log-normal,
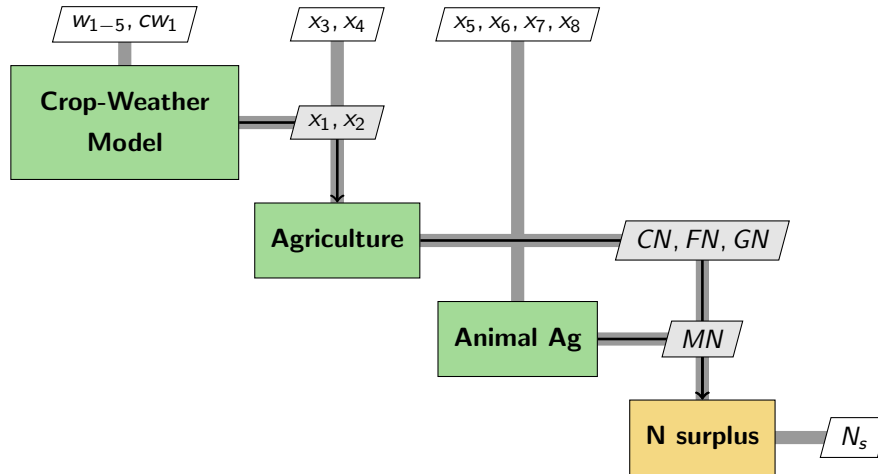

Fig. 7: Extended design structure matrix of Iowa food-water-energy system model.

Table 3: Parameters of the IFEW simulation system model.

Parameter	Description
w_1	July temperature
w_2	July precipitation
w_3	June precipitation
x_4	July-August average temperature
x_5	July-August average precipitation
cw_1	May planting progress
x_1	Corn yield
x_2	Soybean yield
x_3	Rate of commercial nitrogen for corn
x_4	Rate of commercial nitrogen for soybean
x_5	Hog/pigs population
x_6	Beef cattle population
x_7	Milk cows population
x_8	Other cattle population (heifers + slaughter cattle)
CN	Commercial nitrogen (nitrogen in commercial fertilizers)
FN	Biological fixation nitrogen of soybean crop
GN	Grain nitrogen (Nitrogen harvested in grain)
MN	Manure nitrogen (Nitrogen in animal manure)
N_s	Surplus nitrogen in soil

Table 4: Input parameters of the IFEWS simulation model with with variability.

Parameter	Distribution
w_1 (°F)	$N(74,\ 2^2)$
w_2 (in.)	$LogN(0.4,\ 0.4^2)$

respectively. A temperature of 76 °F and a precipitation 2.5 in. are used to divide the distributions into sub-distributions of w_1 and w_2, respectively. The states can be identified as regular temperature (below 76 °F) and high temperature (above 76 °F). Similarly, the states of precipitation are low precipitation (below 25 in.) and regular precipitation (above 25 in.).

Figure 6 shows the decomposed distribution of nitrogen surplus (N_s), i.e., the output parameter of the IFEW system model. The results suggests that the major contribution of nitrogen surplus is coming from regular temperature and regular precipitation of July. Other cases are the combinations of less common weather conditions which lead to extreme amounts of nitrogen surplus but are rare.
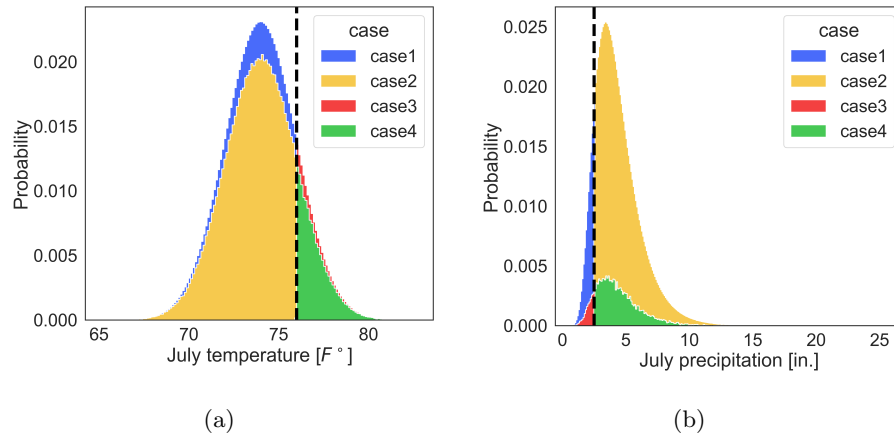
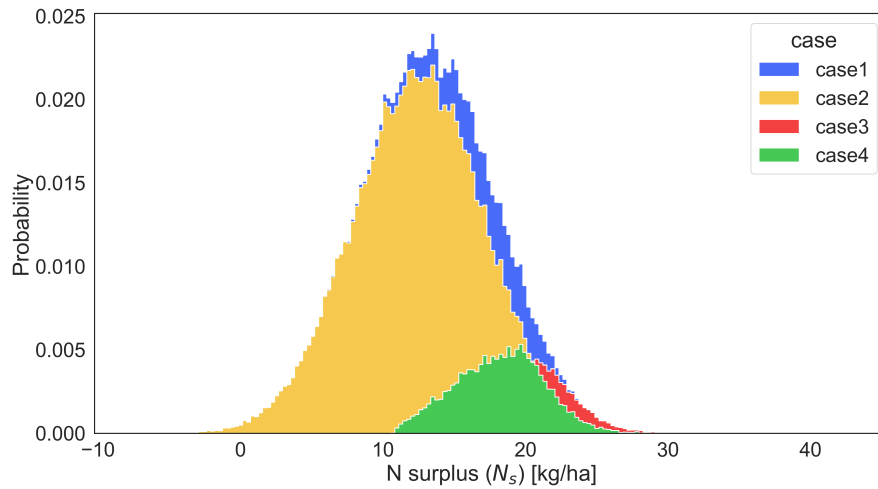**Fig. 8:** Decomposed distribution of input parameters from SD for the IFEW system.

Fig. 9: Decomposed distribution of the nitrogen surplus output of the IFEW system simulation model.

4   Conclusion

This work demonstrates that simulation decomposition (SD) can support the analysis of agricultural and engineering systems involving input parameters of variability. In particular, SD can provide new insights into the effects of the model input ranges on its output. This insight can be useful in understanding cause and effect relations in complex systems. Future work will explore the potential of combining global sensitivity analysis (GSA) with the SD technique.

Furthermore, the use of surrogate modeling in conjunction with those analyses will be investigated to create computationally efficient algorithms for analysis with SD and GSA.

Acknowledgements

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