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Changeable Designs and the Evolution of Value of Infrastructure Systems

Daniel F. Villarraga
Graduate Teaching Assistant, Dept. of Civil and Environmental Engineering, Universidad de los Andes, Bogotá, Colombia

Samuel Torres
Ph.D. Student, Dept. of Civil and Environmental Engineering, Universidad de los Andes, Bogotá, Colombia

Mauricio Sánchez-Silva
Professor, Dept. of Civil and Environmental Engineering, Universidad de los Andes, Bogotá, Colombia

ABSTRACT: Traditional engineering design seeks to maximize the value of infrastructure systems under the assumption that they will remain unchangeable over time. However, this assumption does not describe actual infrastructure's performance over time; and leaves out decisions that stakeholders might take during operation such as scaling, modifying or abandoning the system. Changeability is the systems' ability to change its parameters conveniently in response to unexpected and/or unplanned demands. Including changeability in infrastructure systems valuation and design is important because it increases the system's value and is very efficient in managing risks. This paper presents a model based on stochastic linear programming for the design and the definition of the optimum changeability policy of infrastructure. The results show that considering changeability lead to more valuable systems than the ones conceived through traditional design.

1. Introduction

In an uncertain future, the success (i.e., fulfillment of cost and safety requirements) of long-lasting infrastructure systems can only be achieved through a strategy that allows them to change and/or adapt to new environments that were not envisaged or known before. Thus, the evolution of infrastructure over time is the result of complex interactions between the environment and the stakeholders; and the result unravels over time and cannot be fully predicted at the outset.

Traditionally, systems are over-designed assuring an acceptable performance throughout the time mission. This way, systems can respond to variations in demand but are not able to change their structure, possibly missing out opportunities to add value.

Recently, the term *changeability* has been introduced in engineering design as a way to capture a system's property that helps infrastructure to respond to variable environments generating value within multiple and/or uncertain circumstances (Ross et al., 2008). The inclusion of changeability in design reduces risks associated with long-term uncertainties in comparison with traditional robust designs; and is a mechanism to add value to engineering projects through time. Then, an approach based on the system's ability to change differs unnecessary initial provisions, with the respective costs, reduces uncertainty and can manage unknown scenarios more effectively. In the literature, changeability is found both explicitly (Fitzgerald, 2012), and implicitly included in works related to other "abilities" such as flexibility (Nilchiani, 2009), robustness (Napel et al., 2011), adaptability (Magnani et al., 2013), efficiency (Bordoloi et al., 1999) and modularity (Cardin et al., 2015).

The objective of this paper is to present a linear stochastic programming approach to find changeable design alternatives that outperform traditional-designed systems. In addition, the paper compares the value generated by a traditionally conceived system and a changeable design.

The paper is structured as follows: first, in section 2 we present the concept of changeability and in section 3 we discuss the components of a changeable design. Afterwards, in section 4 we present a general linear stochastic formulation for finding an optimum changeable design. Section 5 presents an illustrative example, and finally, in section 6 we draw some conclusions.

2. CHANGEABILITY

Changeability is the system's ability to modify its structure or operational characteristics. For a change to occur three main elements are needed: i) agent; ii) mechanism; and, iii) effect (Ross et al., 2008). The *agent* is the driving force that causes the change - it could be external or internal to the system. The *mechanism* refers to the process of change ("how"); and the *effect* is the difference between the system states before and after the change takes place. The nature of change could be further characterized, for instance, in terms of its *agility* -i.e., speed of change; the possibility of modifying the structure by adding or removing components (*modularity* and *modifiability*); its *scalability* or capacity for the system to increase or reduce its initial state; and its *efficiency* measured in terms of the relationship between utility and cost of change.

Change may lead to an increment or a loss in the system's value over time. Frequently, the latter is referred to as *deterioration* (Sánchez-silva and Klutke, 2016); however, in this paper we are mostly interested in changes that add value to the system and changeability will be related to those types of changes. These changes may be temporal or permanent. In the first case, the system's state changes for a relatively short time period and then returns to its original state; in the second case, changes last for long time periods. Note that the concepts of "short" or "long" time periods depend on the nature of the system.

Therefore, the change process could be described by figure 1. In this figure, A denotes the agent driven the change, $X(t)$ describes the system properties at some time t and M is a mechanism of change. Note that a system might have multiple agents capable of driven change, diverse mechanisms that could be instigated and multiple possible end states at every time t.

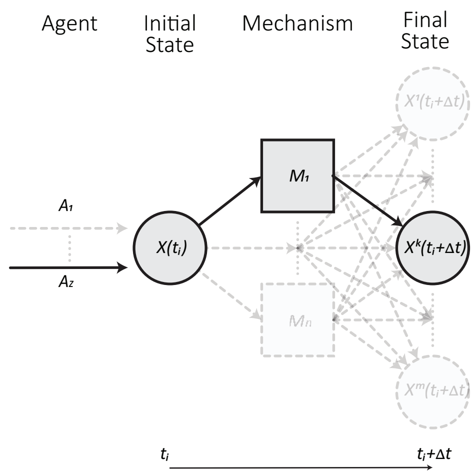

Figure 1: Change implementation and its components.

Additionally, agents are motivated to drive change by the presence of a changeability trigger. Changeability triggers fall in three categories: i) Safety Requirements, ii) Operational Requirements, and iii) Utility Requirements. What's more, a trigger motivates an agent to drive change by the observation of a determined interesting value for the stakeholders (i.e. Demand of the system), so, changeability triggers are present whenever systems are controlled.

Moreover, the concept of changeability may be divided in two components: Potential Changeability C_{p_i}, and Effective Changeability C_{e_i}. The potential part describes the possibility of change that a determined property i of the system have, while the effective part relates to the implementation of changes in property i trough the service life of the system. Numerically, for properties measured in ordered spaces, the potential changeability of property i is proportional to the extend of the possibility of change $s_i(t)$ and inversely proportional to the cost of change implementation $c_i(\Delta x_i(t))$; i.e.,

$$C_{p_i}(t) \propto \zeta \frac{s_i(t)}{c_i(\Delta x_i(t))} \tag{1}$$

3. Designing for changeability and changeability policies

According to the definition of changeability, a changeable design is composed by two primary components: i) the initial values for the system properties, and ii) the potential or optioned values that the system's properties could take if a changeability trigger is reached at any time through the service life.

On the other hand, a changeability policy determines how the modification of the system's properties take place. It should specify the changeability triggers and the specific actions required once they are reached (i.e the modification by x units of property y). Moreover, changeability policies related to property i determine the way of harnessing the potential changeability C_{p_i} of i and, thus, affect directly the effective changeability C_{e_i} of such property, described as $C_{e_i}(t) = C_{p_i}(t=0) - C_{p_i}(t)$.

In figure 2 illustrates how changeability policies work related to an specific changeable design. It shows the demand and the the evolution of a system's property x_i. The changeability policy is specified by a changeability trigger d_t related to the demand $d(t)$ and the amount ΔX_i on which the property X_i is modified.

To sum up, a changeable design is determined by the initial design (properties of the parameters at time $t=0$), which in turn define the potential changeability; and by a changeability policy, which is a pair consisting of a changeability trigger (i.e the driver a change) and the desired *effect* of the change.

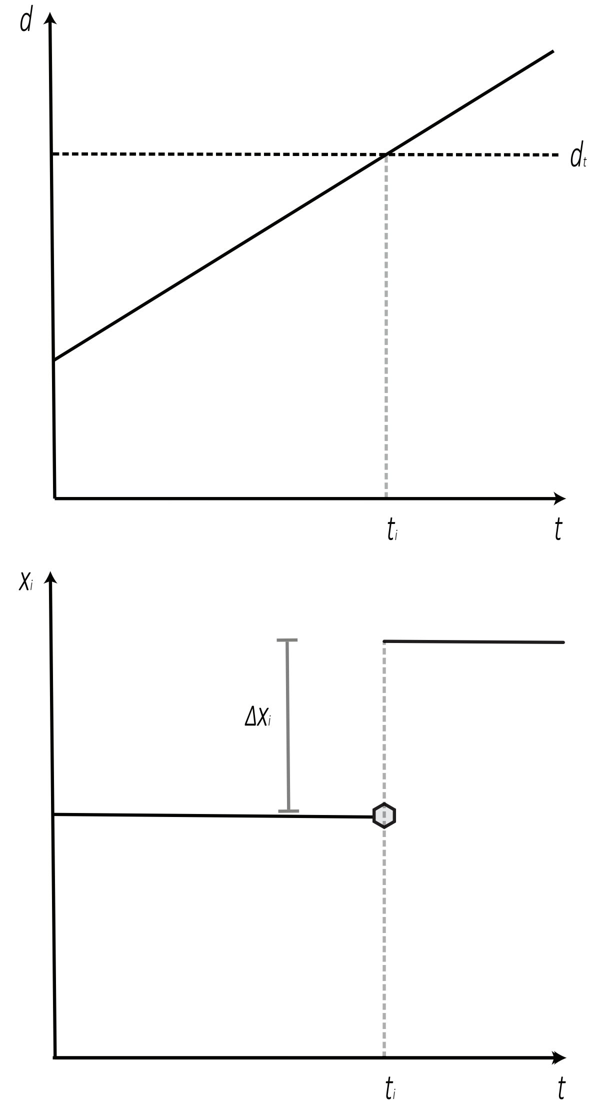

Figure 2: Changeability trigger based upon the system demand d, and its effect ΔX_i upon the system's property X_i.

4. Linear stochastic program formulation

Lets consider a system conceived to operate through large time windows T over which it is subject to multiple sources of uncertainty; then, future demands and operation requirements are not known to stakeholders. However, it is important to notice that there are certain future times t when the realizations of uncertain variables are observed. Let's further assume that that uncertain variables are characterized by stochastic processes modeled as Markov Processes. Therefore, at every time t there are expected values for the uncertain variables at time $t+1$.

Infrastructure systems are defined by a set of parameters $Y = [Y_1, Y_2, ..., Y_n]$ that may change over time due to, for example, variations in their physical properties or as a result of stakeholders' decisions such as scaling. A change on the systems properties is denoted by a decision vector $x = [x_1, x_2, ..., x_n]$. Let's further define the vector $x_t = [x_{1_t}, x_{2_t}, ..., x_{n_t}]$ as the decisions on the system state $y_t = [y_{1_t}, y_{2_t}, ..., y_{n_t}]$ at time t. The state Y_t and decision X_t vectors have the same size, and a decision of not changing the system's properties at time t is given by $X_t = Y_t$.

The state evolution and the relationship between X_t and Y_t is illustrated in Figure 3. Circles are used to illustrate the state of the system due to its uncontrolled evolution, while squares denote changes on the system's state due to decisions made by the stakeholders. The uncontrolled evolution of the system state might follow a stochastic process; for that reason, in figure 3 possible state (dotted lines) and actual state (solid lines) paths are shown.

Every change on the system's structure have a cost $C(x_t, y_t)$ that depends on the magnitude of the change $(x_t - y_t)$. In this paper it is going to be considered a case where systems' properties are described by continuous variables and decisions could only enlarge them ($X_t \geq Y_t, \forall t$). That assumption is only taken to simplify the model but it does not mean that other types of variables or decisions could not be considered.

As a result of the system's operation, stakeholders get a utility $U(Y, d)$, which is a function of the state of the system and some demand d, i.e number of cars passing through a highway. Furthermore, there is a cost of failure $C_x(Y, Y_{lim})$ that materializes if the system's state falls below a threshold Y_{lim}, a cost $C_v(V(Y), V_{lim})$ when the system performance $V(Y)$ violates a limit V_{lim}, a cost for operating the system $C_p(Y_t)$ given by the system's properties; and finally a cost $C_d(K(Y_t), d_t)$ when the system's capacity $K(Y_t)$ doesn't meet the demand d_t.

It is reasonable to assume that stakeholders want to maximize the value of their decisions. Then, every decision is made based upon the observation

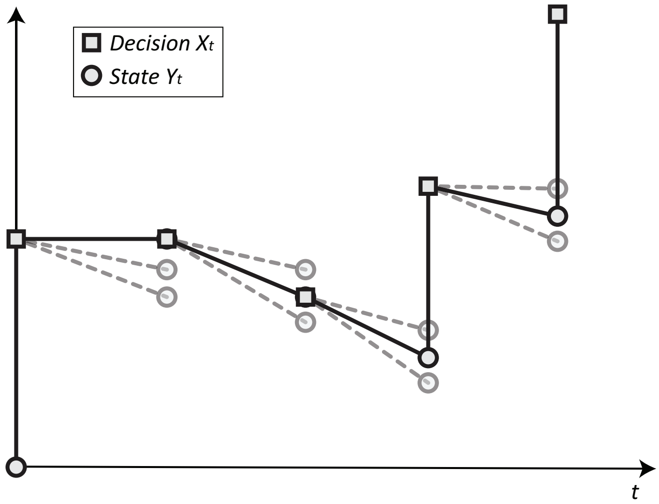

Figure 3: State y_t of the system over time and decisions x_t made upon it.

of the system's demand and its expected state at the following time observation. Then the objective function can be defined as

$$
\begin{aligned}
z = \max \frac{1}{N} \sum_{n=1}^{N} \sum_{t=0}^{T-1} & \mathbb{E}\,(U_{t+1}(Y_{t+1}, D_{t+1}) \\
& - C_x(Y_{t+1}, Y_{lim}) \\
& - C_v(V(Y_{t+1}), V_{lim}) - C_d(K(Y_{t+1}), D_{t+1}) \\
& - C_p(Y_t) | X_t = x_t, D_t = d_t) \cdot e^{-\lambda \cdot (t+1)} \\
& - C(x_t, y_t) \cdot e^{-\lambda \cdot t}
\end{aligned} \tag{2}
$$

subject to:

$$y_{n_0} = 0, \forall n \tag{3}$$

$$\delta_{n_0} = 0, \forall n \tag{4}$$

$$y_{n_t} = x_{n_{t-1}} - \delta_{n_t}, \forall t \geq 1, \forall n \tag{5}$$

$$x_{n_t} \geq y_{n_t}, \forall t, \forall n \tag{6}$$

Note that in this case, the time horizon of the system T is dived in a set of discrete system observation times. Also, the analysis considers a set of N demand scenarios. Finally, all future costs are discounted at a rate of λ.

The restrictions to the linear stochastic program are shown through equations 3 to 6. Restrictions in equations 3 and 4 declare that at the beginning the system's properties state is zero and unwanted changes δ_t at that time have not take place. In Equation 5 it is assured that the system's state is updated due to unwanted changes δ_t and decisions x_t. Finally, equation 6 guarantees that decisions made upon any system property should imply a system state improvement.

As could be noted from equation 2, this formulation does not follow a nested structure as the one typically found in multi-stage linear programming (Shapiro et al., 2009). Instead, is an extension of a two-stage linear stochastic programming (Shapiro et al., 2009), and it is based upon the assumption that stakeholders seek optimum value trough each decision looking forward in time just one period. However, taking into account that the size of a time period could be arbitrarily selected, this formulation should fit most cases.

For the sake of simplicity, in this paper we limit our example to the consideration of utility U, change implementation costs C and costs for not meeting the demand of the system C_d. Also, we don't include unwanted changes δ on the system's properties X. Nevertheless, a complete model could be derived from the formulation presented in this section.

5. Design alternatives for an office building

Consider the design of an hypothetical office building upon which stakeholders will derive their utility $U(t)$ from the rent of each floor, as follows:

$$U(t) = 480000 \cdot d(t), \forall t > 0 \tag{7}$$

where $d(t)$ denotes a realization of the demand process D at time t; which is defined as follows:

$$D(t) = D_i + \sum_{k=1}^{t} \varepsilon_k, \forall t > 0 \tag{8}$$

with $D_i - N(\mu = 20, \sigma = 2)$; and e_k follows a normal distribution with $N(\mu = 1, \sigma = 3)$.

Stakeholders expect the building to operate trough a time window of $T = 50$ years. The system state and the demand is measured every year and a decision is made upon the expectation of the next period demand $\mathbb{E}(D(t+1))$.

The construction of the building has an initial cost $C_i = 90000 \cdot x_p + 4000000 \cdot x_i$ proportional to the potential x_p and initial x_i number of floors. In other words, the cost C_i consists of the cost of the foundation (i.e. the maximum size of the building/its potential changeability) and the cost of construction.

Every intervention made after $t = 0$ have a cost $C(x_t, y_t)$ proportional to the size of the intervention $x_t - y_t$; i.e.:

$$C(x_t, y_t) = 4000000 \cdot (x_t - y_t), \forall t > 0 \tag{9}$$

Moreover, stakeholders desire that the office building completely cover the demand $d(t)$ at every time t. So, there is a high cost for not being able to fulfill the demand $d(t)$, which is given by:

$$C_d(d_t, y_t) = k_d \cdot (d_t - y_t), \forall t > 0 \tag{10}$$

where k_d is a penalization cost. There is going to be considered a discount rate of 2% for bringing future monetary values to the present. Additionally, due to the nature of the problem, interventions should be at least 5 years apart and their size of a minimum of 5 floors.

5.1. *Traditional design*

As discussed before, traditional design conceives unchangeable systems. In this case, this approach allows the office building to have only one investment at the beginning of the service life ($t = 0$). For this design, we consider the distribution of the demand at the end of the service life and select a number of floors with 5% of exceedance at that time. The distribution of the demand $D(T)$ is shown in figure 4. Thus, the building should be designed for 106 floors.

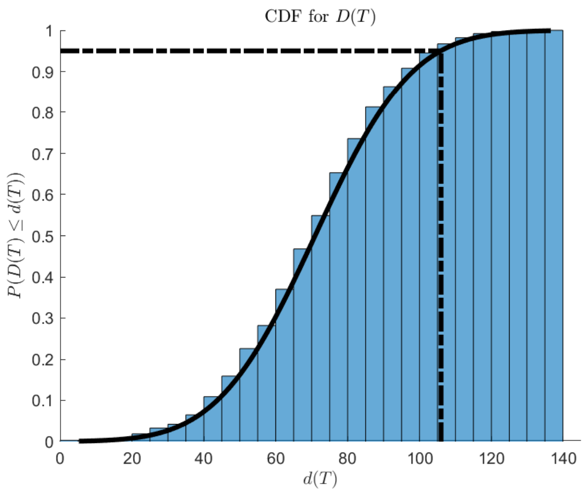

Figure 4: Distribution of the demand $D(T)$

5.2. *Changeable design*

The first objective of changeable design is to define the initial design parameters. For that purpose, we consider a thousand possible demand scenarios; i.e., $N = 1000$. Then, for different values of k_d (Equation 10) there are different optimum initial designs. In figure 5 the black line corresponds to k_d of one million dollars and the green line to zero. The solid red line corresponds to the expected value for the demand, while the dashed red lines are the lower and upper bounds after thousand Montecarlo Simulations.

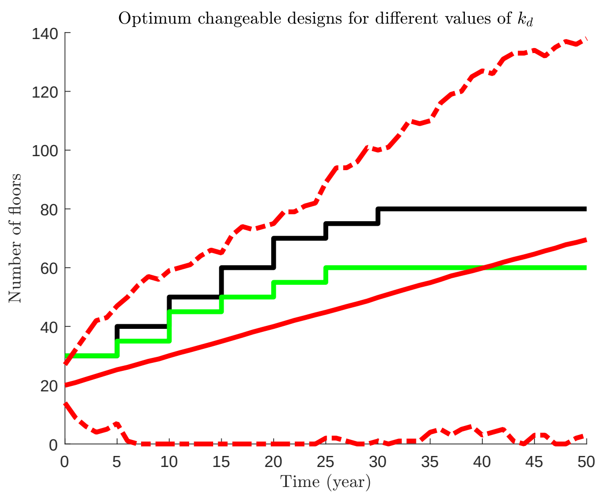

Figure 5: Optimum changeable designs for different values of k_d

The values for x_i and x_p for each value of k_d are shown in table 1. It is important to note that the generic behavior delivered by the solution to the linear stochastic program should not be taken as a change policy because it does not depend on any changeability trigger, on the contrary it relies blindly on the expected values for the demand given by all scenarios considered.

Table 1: Optimum changeable designs for different values of k_d

k_d [10^6 USD]	x_i	x_p
1	30	80
0	30	60

Figure 6 shows the generic behavior of the solution for $k_d = 1$ million USD, a particular scenario and the systems response with a change policy. As it is shown, the response with a change policy avoids the implementation of unnecessary changes based upon the realization of the uncertain demand.

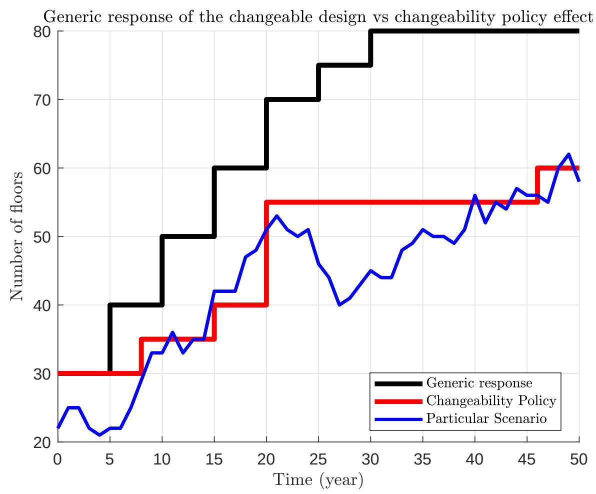

Figure 6: Generic behavior of the solution against a changeability policy for $k_d = 1$ million USD.

5.3. *The value of changeable vs traditional design*

The comparison of the different designs is carried out using a policy such as the one implemented in figure 6. The trigger of that policy is an expected value at $t+1$ greater than the present number of floors at t. The updating of the number of floors is done to meet the expected demand at $t+1$ in groups of 5 floors and the changes are limited to occur at least 5 year apart.

For both values of k_d, a better economic performance is expected for the changeable designs. Figures 7 and 8 show the histograms for the difference of the NPV between the changeable (NPV_c) and the traditional (NPV_t) designs. Additionally, table 2 presents the expected value of such difference. Note that for $k_d = 1 \cdot 10^6$ USD, the expected NPV of the changeable design $\mathbb{E}(NPV_c)$ is 2.15 times bigger than the expected NPV of the traditional design $\mathbb{E}(NPV_t)$; for $k_d = 0$ the relationship of the expected NPV $\mathbb{E}(NPV_c)/\mathbb{E}(NPV_t)$ is 2.10.

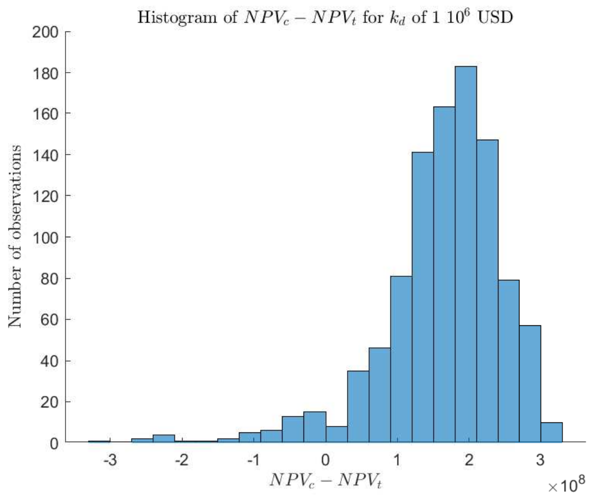

Figure 7: Histogram of the difference between the NPV for changeable and traditional designs, $k_d = 1$ million USD.

Table 2: Expected value of the difference between the NPV for changeable and traditional designs.

k_d [10^6 USD]	$\mathbb{E}(NPV_c - NPV_t)$ [10^6 USD]
1	163.74
0	194.09

6. CONCLUSIONS AND RECOMMENDATIONS

This paper presents a model based on stochastic linear programming for the changeable design selection and the definition of the optimum changeability policy of infrastructure systems. The results show that by considering changeability it is possible to

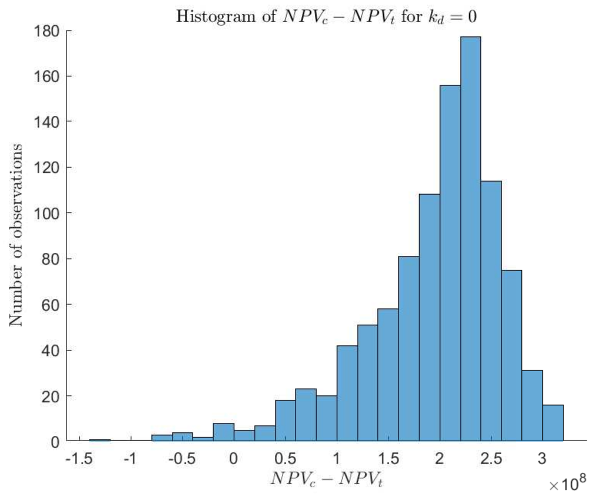

Figure 8: Histogram of the difference between the NPV for changeable and traditional designs, $k_d = 0$.

add value to infrastructure systems when compared with traditional design.

Changeability is implemented using a linear stochastic formulation of the decisions made through time. The approach presented is general and could be adapted to the design of any infrastructure system depending on the problem restrictions. The formulation is based upon the assumption that stakeholders would seek optimality trough each decision looking forward one period in time.

The solution to the linear stochastic program provides the optimal design; which consists of the value of the parameters at $t = 0$, and the extend to which those parameters should be able to change. The optimality of a policy as such is difficult to define and is against the basic principle of changeability; the central point is to guarantee the existence of the policy within the context of the interests of stakeholders.

As shown, changeable designs are expected to deliver more value than traditional designs. In the example presented in this paper changeable designs deliver more than twice the value of a traditional design. Future works should focus on the application of this approach for finding the optimal changeable design of systems with multiple properties, with more than one changeability trigger and subject to unwanted changes.

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