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Probabilistic cost prediction for submarine power cable projects

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ABSTRACT

It is estimated that Europe alone will need to add over 250,000 km of transmission capacity by 2050, if it is to meet renewable energy production goals while maintaining security of supply. Estimating the cost of new transmission infrastructure is difficult, but it is crucial to predict these costs as accurately as possible, given their importance to the energy transition. Transmission capacity expansion plans are often founded on optimistic projections of expansion costs. We present probabilistic predictive models of the cost of submarine power cables, which can be used by policymakers, industry, and academia to better approximate the true cost of transmission expansion plans. The models are both generalizable and well-specified for a variety of submarine applications, across a variety of regions. The best performing statistical learning model has slightly more predictive power than a simpler, linear econometric model. The specific decision context will determine whether the extra data gathering effort for the statistical learning model is worth the additional precision. A case study illustrates that incorporating the uncertainty associated with the cost prediction to calculate risk metrics - value-at-risk and conditional-value-at-risk - provides useful information to the decision-maker about cost variability and extremes.

1. Introduction

The first submarine power cable used for electricity transmission was commissioned in 1954, connecting the electric grid of Gotland Island to Sweden's mainland grid. The cable was rated at 20 megawatts (MW), traversing a submarine route length of 98 kilometers (km) [1]. On the opposite end of the spectrum, the proposed EuroAsia Interconnector would connect the electricity grid of Israel to Greece via Cyprus, with a total rated transmission capacity of 2000 MW, traversing a submarine route length of over 1500 km, at a maximum depth of over 2700 m. The most ambitious to date, this submarine cable project has an estimated cost of 1.5 billion euros [2].

Over the past fifty years, submarine power cables have been employed in diverse applications, including: crossing bays, lakes or rivers; providing supply to islands from mainland grids; sharing supply between islands; interconnecting national grids; providing supply to offshore oil and gas rigs; and, most recently, for offshore wind power connection [1].

Both offshore wind power and national-level grid interconnections - in the seas of Northern Europe and the Mediterranean - figure heavily in the European Union's (EU) plans for achieving ambitious renewable energy goals. In Germany, the North and Baltic seas alone are seeing the construction and operation of 33 offshore wind farms, totaling 13.5 Gigawatts (GW) of capacity [3,4]. The push for renewable production is not limited to Europe: and so, worldwide, the submarine power cable industry is expected to grow by 45% in the next decade [5].

1.1. Cost estimation techniques

When project cost estimation is conducted in the planning phase of large infrastructure projects, it is usually done through *Unit Cost Estimation* (UCE) [6]. This method requires a cost estimate for each unit or process being built, as well as knowledge of the unit's depreciation rate, salvage value, expected lifetime, and expected repair and maintenance costs. An informative example of this method of cost estimation is illustrated in [7]. As in most engineering economic models, these cost estimates are based on the expected values of the costs of many individual components. This is problematic because it does not account for the uncertainty surrounding each individual input cost, or how the costs relate to each other; positively correlated costs compound uncertainty, but negatively correlated costs can reduce uncertainty. Thus, using expected value inputs does not guarantee an expected value output of a UCE model.

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Industry has attempted to minimize the uncertainty in input values by annually updating unit cost reference books, such as the *RS Means* [8]. These volumes catalog the material, labor (number of crew needed, daily output expected, labor-hours, etc.), and equipment needs for specific sub-projects. The project engineering team must determine what sub-project tasks will make up the entire project cost (e.g. for large electrical infrastructure projects, such sub-projects could include generation equipment installation, inverter installation, transmission line installation, etc.). Despite the great detail of such cost reference books, these reference volumes are of limited use, as they are proprietary, region-specific point-estimates that are usually developed only for specific deployment options. For example, while *RS Means* publishes a yearly review of electrical cost data with estimates for underground and overhead transmission line construction work, estimates for the costs associated with submarine power cable projects are not included [8].

Because detailed, and presumably more accurate data, is too often proprietary, researchers have recently studied how to apply statistical methods to infrastructure project cost estimation. With more sophisticated mathematical models, a reasonably accurate cost estimate could be made with less detailed input data.

1.2. Early cost prediction for infrastructure planning

Infrastructure planning is a major undertaking, with just the planning phase typically spanning years. To determine the potential feasibility of an infrastructure project, an estimate of the project cost is needed fairly early in the planning stage, when specific project details are not fully known. However, it is in the early planning stages that management decides whether or not to proceed with a project. Thus, it is imperative to have the cost estimated as early and as accurately as possible.

To this end, several types of infrastructure projects have utilized methods in statistical learning for early cost prediction. These methods include linear regressions, classification trees and artificial neural networks, applied to various infrastructure projects such as metro network planning [9], bridge construction [10], highway projects [11], and road reconstruction [12].

The statistical methods used in these studies have been applied to either small data sets of projects ($n = 12–18$) [9,11], or to data sets within a specific region [10,12,13]. The results of model-fit from such data sets can seem excellent (with R^2 values of greater than 0.9), but are usually too optimistic, as such a model is not generalizable to many other cases.

In this paper, we develop probabilistic models to support early cost prediction for submarine power cable projects. The final models presented in Section 3 are based on a global database of 61 submarine cable projects. This makes the models both generalizable and well-specified for a variety of applications (i.e. submarine power cable projects for island supply, offshore wind farm connection, and grid interconnection, *inter alia*), across a variety of regions.

1.3. Paper structure

The structure of the paper is as follows. Section 2 describes the global submarine power cable project database. Section 3 elaborates on the statistical learning methods applied to the data set. Section 4 details the predictive accuracy of the final models. Section 5 applies the final models to a case study on submarine power cable replacement for Vancouver Island, Canada.

2. Data

The data is based on a privately maintained submarine power cable project database [14]. At the time of this study, the database contained a record of 296 projects, with each record comprised of various project features. Data collected included project attributes like the power (MW) and voltage (kV) of the submarine cable, manufacturer, armoring material, and insulation type. Of the 36 project attributes sought, 22 were reported with sufficient frequency to enable collection for a large number of projects. The contract cost of the submarine power cable project was also collected for 106 projects.

The data was verified through a significant effort of cross-referencing sources of project details: from company press releases to industry technical reports and presentations. When not reported in the company press release, the maximum depth of the cable route was obtained from bathymetry maps. After the verification of the 296 project records, it was determined that the data for only 61 projects could be reliably substantiated. To reduce the variability in the cost data, only costs reported in press releases from manufacturers were used (e.g. [15]).

2.1. Project attributes

There are many features of a project that can affect its cost. For submarine power cable projects, materials costs, such as the cost of copper or aluminum used in the conductor, is thought to be a large contributor to project cost. Thus, project attributes that represent material cost were collected such as, the number of conductor cores in each cable (one core for direct current (DC) and three cores for alternating current (AC)); the cross-sectional area of the conductor in square-millimeters; the type of current (AC or DC); the number of cables; the length of the submarine route of the cable (s); the type of conductor (copper, *Cu*, or aluminum, *Al*); the voltage (kV) and power (MW) of the cable; and the market price of copper.

Project attributes aimed at approximating the equipment cost of a submarine power cable project included: the cable laying vessel used; the maximum depth along the submarine route; and the application for which the cable will be used (island supply; grid interconnection; offshore wind power; bay/lake/river crossing; or oil and gas offshore platform power supply).

Market conditions for labor costs were approximated by the following project attributes: country of project; manufacturer of the submarine cable; cable customer; contract year; and estimated project length in years.

2.2. Data transformation and variable selection

Finally, the contract cost for each submarine power cable project was converted to real values in 2012 USD [16]. The natural logarithm of the cost is used as the dependent variable in all models presented in Section 3, due to its normality. Modeling the cost data as a Gamma distribution did not improve predictive performance.

As described in Section 3, many different statistical models were tested with different combinations of the 21 aforementioned project attributes. Table 1 details the project attributes, the inclusion of which resulted in the best prediction of project cost. The most useful attributes from this perspective were eight continuous variables and three categorical variables.

3. Model development and selection

The primary research question of this work is to determine the best statistical model for submarine power cable cost prediction. Industry insight on predictors was obtained through conversations