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A framework for geometric quantification and forecasting of cost uncertainty for aerospace innovations

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ABSTRACT

Quantification and forecasting of cost uncertainty for aerospace innovations is challenged by conditions of small data which arises out of having few measurement points, little prior experience, unknown history, low data quality, and conditions of deep uncertainty. Literature research suggests that no frameworks exist which specifically address cost estimation under such conditions. In order to provide contemporary cost estimating techniques with an innovative perspective for addressing such challenges a framework based on the principles of spatial geometry is described. The framework consists of a method for visualising cost uncertainty and a dependency model for quantifying and forecasting cost uncertainty. Cost uncertainty is declared to represent manifested and unintended future cost variance with a probability of 100% and an unknown quantity and innovative starting conditions considered to exist when no verified and accurate cost model is available. The shape of data is used as an organising principle and the attribute of geometrical symmetry of cost variance point clouds used for the quantification of cost uncertainty. The results of the investigation suggest that the uncertainty of a cost estimate at any future point in time may be determined by the geometric symmetry of the cost variance data in its point cloud form at the time of estimation. Recommendations for future research include using the framework to determine the "most likely values" of estimates in Monte Carlo simulations and generalising the dependency model introduced. Future work is also recommended to reduce the framework limitations noted.

Contents

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1. Introduction

Increasing technology innovation, competition and regulation are raising the pressure on aerospace organisations to innovate their portfolios in an accelerated manner. These conditions are driving the growth of complexity and financial uncertainty in respect to the whole product life cycle cost. This then leads to innovation hesitance which slows the discovery and deployment of the innovative aerospace solutions required for the society of today and tomorrow. "Innovative" is hereby understood as a condition of products or services where no verified and accurate cost model exists.

One significant aspect of innovation hesitance is related to the challenges of forecasting the cost variance propagation of the technical baseline estimate across the whole product life cycle. Respecting that different types of uncertainty exist and require differentiation [1–5]. The investigation defines cost uncertainty as manifested and unintended future cost variance with a probability of 100% and an unknown quantity. This allows for a clear differentiation from the concept of risk where the probability of an unintended event is $<100\%$ [2] and an estimate of probable impact exists. While the management of uncertainty is subject to various essentially similar industry standards [6–11]. These generally apply regression based estimation approaches to products which do not address conditions of small data. Conditions of small data arise when few measurement points, little prior experience, no known history low quality data and deep uncertainty are present [12–16]. Two fundamental forecasting approaches exist in forward and inverse uncertainty propagation. Forward uncertainty propagation depends on the existence of propagation rules derived through regression approaches. Inverse propagation (or hybrid approaches) cannot be considered since these serve a monitoring purpose. Indeed, if the amount of regressible data available for cost estimation does not admit the use of techniques relying on the Central Limit Theorem then no alternatives appear available [17–20].

In light of lacking alternatives the opportunities of spatial geometry to address the small data challenge are investigated. As illustrated in Fig. 1 standard regression techniques find their applicability when analysing amounts of data commonly found in practice yet become less and less effective as this amount moves to big data. In big data we then see applications of geometrical approaches growing. A good example of this is the large volumes of data encountered in engineering simulations. In a similar manner it is suggested that spatial geometry can be applied in the analysis of small data.

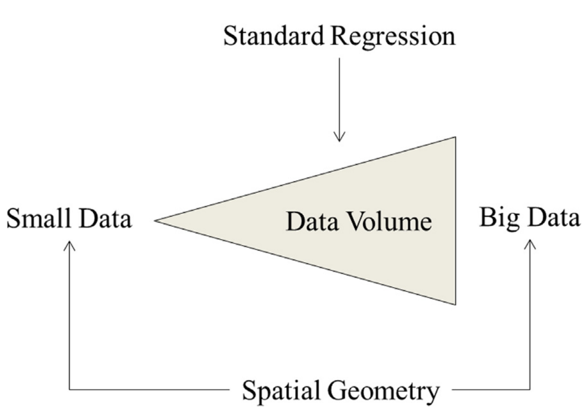

Fig. 1. Application areas of spatial geometry for data analysis.

The framework contributes to knowledge by providing an alternative to Central Limit Theorem techniques for quantifying cost uncertainty propagation for small data through a repeatable process based on the principles of spatial geometry.

The potential benefit to industry is the ability to forecast the propagation of cost variance based upon small data. This is accomplished without dependency on expert opinion, analogies or application of standard regression approaches that rely on the Central Limit Theorem. This stands in marked contrast to current practice where the cost estimate uncertainty is estimated without reference to a relevant time-window or determination of a decay rate for accuracy.

Section 2 introduces the concepts of spatial geometry and the role of symmetry in its description. Section 3 covers the results of the literature review and Section 4 describes the data context analysed. Section 5 provides a detailed description of the framework, including the research methodology, the principle activities related to visualisation, quantification and validation. Section 6 applies the framework to case study data for correlation purposes. Section 7 explores the interdependency of the cost variance dimensions of the case study data. Section 8 validates the results of the investigation including a results comparison, expert opinion and the contribution to knowledge and potential benefits to industry. Section 10 provides a conclusion and recommendations for future work. The theoretical foundations are explored primarily in Sections 2 and 3 while the applied perspective is shared in Sections 4, 5, 6 and 7. Sections 8 and 9 are primarily concerned with a discussion of the research results and potentially valuable directions of future research.

2. Spatial geometry and the role of symmetry

When faced by small data the estimator is essentially given no or little information at $t=0$ regarding the (estimated) variance for at least three cost variance dimensions at time$=0$ (i.e. due to changes in engineering requirements, cost estimation principles or schedule) and needs to forecast the cost variance at time$=1$–n. For purposes of the study the estimation of uncertainty from the perspective of spatial geometry with less than three cost dimensions is declared to be feasible only with sufficient prior information which admits the use of regression techniques based on the Central Limit Theorem. Mathematically two fundamentally different approaches exist for the estimator; the arithmetic and the geometric. The validity of this alternative is seen supported by one of the founding fathers of modern statistics, Karl Pearson, who states "Most statistical conclusions which can be obtained by arithmetic, can also be achieved by geometry, and many conclusions can be formed which it would be difficult to reach except by geometry." [21]. The arithmetic perspective focuses on the interdependencies of individual data points themselves (as seen for example in the cost estimating relationship models used in parametric estimation techniques) while the perspective of spatial geometry describe the behaviour of the space created by connecting peripheral data points as illustrated by Fig. 2.

Arithmetic perspective Geometric perspective.