A BAYESIAN NETWORK FOR QUANTIFYING UNCERTAINTY FOR DISTRIBUTION PLANNING MODEL

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Uncertainty is a key issue in engineering design [1]: optimal solutions generally do not involve safety margins, but real systems involve having uncertainty, variability, and error. For example, geometry, material parameters, boundary conditions, or even the model itself includes uncertainty. To provide safe designs, uncertainty must be considered in optimization models.

There are different ways to introduce uncertainty into the model design: the most popular are interval methods, fuzzy variables, and probabilistic modeling. Each approach has its particularities, advantages, and disadvantages. Here, we focus on the probabilistic approach based on Bayes' theorem, which is used in situations where quantitative statistical information on variability is available. When the probabilistic approach is used, the variability is modeled using random variables.

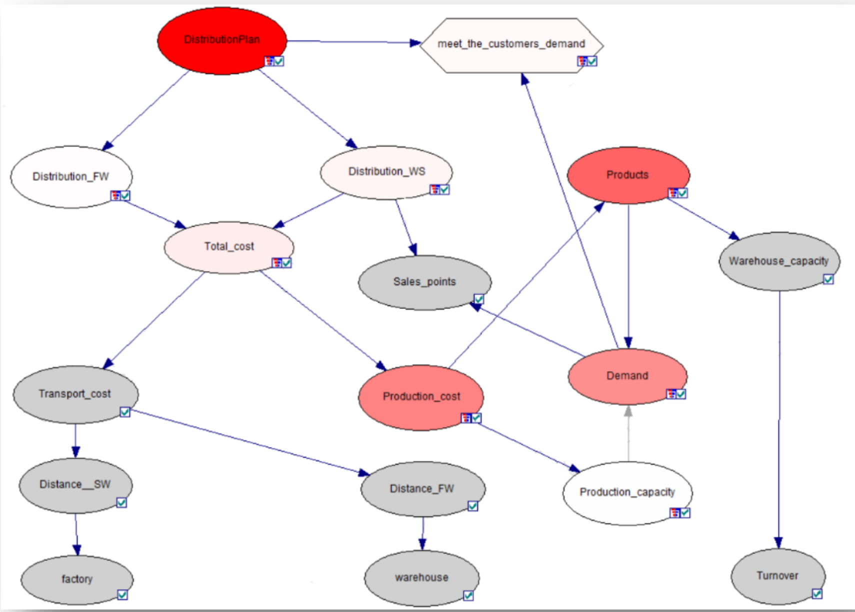

Figure 1 Bayesian Network for a Distribution Planning System, modified from Loera et al. [5]

In the context of decision making, it is important to take into account the uncertainty that exists in the context of distribution planning. For example, if demand is higher than expected, there may be insufficient distribution capacity to meet it, or if it is smaller, some assets may be considered in retrospect stranded. A planning model can be difficult to solve, due to its high level of complexity and the number of optimal solutions possible in a large data set.

When these large data sets are combined with complex algorithms, such as deep neural networks, machine learning, genetic algorithms. However, despite the success of these models, not much attention has been given to quantifying uncertainty (UQ); that is, quantify the confidence of a model in its predictions. In some situations, UQ may not be a high priority, for example, in recommending movie titles, gauntlets [3] or any other personal situation. But in situations where incorrect prediction is a matter of life and death, UQ is crucial. For example, if military personnel in combat use a Mixed Linear Programming Models (MILP) algorithm to make decisions, it is vital to know how secure the algorithm is in their predictions.

There is a productive way to perform a UQ and obtain reliable results and with wide applications, it is the application of a Bayesian network. Here the idea of quantifying with the application from a Bayesian Network (BN), since the vision of probability as an expression of a state of knowledge has profound consequences. This probability perspective is called conditional probability or Bayesian probability. Causal probability networks are a well-established graphical format for coding conditional probabilistic relationships between uncertain variables. The nodes of a BN represent variables and the arcs represent causal or influential relationships between them. The BN is based on solid bases of causality and probability theory; namely, the Bayesian probability [4] See figure 1.

A strength of the BN is that it explicitly includes the element of uncertainty related to any strategy or decision. Links are based on available data. This may be a large data set, the output of a model, or, in the absence of data, it may be based on expert opinion. And it represents a new way of quantifying uncertainty.

There are studies that conclude that with this technique it is possible to quickly and efficiently perform the UQ in a mixed-integer linear programming model (MILP) [5] for problems of planning the distribution of consumer goods, saving time and computer resources, making the decision-making process efficient, it also contributes to the process so that the decision-maker makes it with certainty and objective confidence of the error associated with making the decision, that is, of the probability of making an optimal decision wrongly a linear programming model. An optimal decision within the model that is highly dependent on the particular choice of scenarios rather than the underlying uncertainty in the model inputs. In conclusion, from a BN, the UQ of a distribution problem can be estimated, regardless of the amount of demand and products, as well as facilities.

REFERENCES

[1] CURSI, EDUARDO SOUZA DE, AND RAFAEL HOLDORF LOPEZ. “UNCERTAINTY QUANTIFICATION IN OPTIMIZATION.” ADVANCES IN INTELLIGENT SYSTEMS AND COMPUTING OPTIMIZATION OF COMPLEX SYSTEMS: THEORY, MODELS, ALGORITHMS AND APPLICATIONS, 2019, 557–66. HTTPS://DOI.ORG/10.1007/978-3-030-21803-4_56.

[2] OPATHELLA, CHANDRABHANU, AYMAN ELKASRAWY, AMR ADEL MOHAMED, AND BALA VENKATESH. “MILP FORMULATION FOR GENERATION AND STORAGE ASSET SIZING AND SITTING FOR RELIABILITY CONSTRAINED SYSTEM PLANNING.” INTERNATIONAL JOURNAL OF ELECTRICAL POWER & ENERGY SYSTEMS 116 (2020): 105529. HTTPS://DOI.ORG/10.1016/J.IJEPES.2019.105529.

[3] MISHRA, SRIKANTA, AND AKHIL DATTA-GUPTA. “UNCERTAINTY QUANTIFICATION.” APPLIED STATISTICAL MODELING AND DATA ANALYTICS, 2018, 119–67. HTTPS://DOI.ORG/10.1016/B978-0-12-803279-4.00006-7.

[4] CONSTANTINOU, ANTHONY COSTA; FENTON, NORMAN; NEIL, MARTIN: INTEGRATING EXPERT KNOWLEDGE WITH DATA IN BAYESIAN NETWORKS. EXPERT SYSTEMS WITH APPLICATIONS, ISSN: 0957-4174, VOL: 56, PAGE: 197-208. (2016)

[5] LOERA-CASTRO, ADRIAN-FRANCISCO; GARCÍA-CASTELLANOS HUMBERTO; AND OCHO-ZEZZATTI, ALBERTO .” QUANTIFICATION OF UNCERTAINTY IN THE PLANNING OF THE DISTRIBUTION OF CONSUMER GOODS USING A BAYESIAN NETWORK”. *DYNA Management*, Jan-Dec 2020, vol. 8, no. 1, [2p.]. DOI: HTTP://DX.DOI.ORG/10.6036/9571