Value Based Decision Control for Complex Systems

Yuri Pavlov
Bulgarian Academy of Sciences, Institute of Information and Communication Technologies, Bulgaria

INTRODUCTION

The mathematical description of Decision maker (DM) analytically as utility function together with the model description of the investigated process could give a complete mathematical representation of the complex system "Technologist (DM) – dynamic process." Such models ensure exact mathematical descriptions of problems in various areas which quantitative modeling is difficult: economics, biotechnology, ecology, and so on. These models guarantee that the powerful optimal control theory could be applied in such complex areas and exact mathematical solutions could be determined in agreement with the DM preferences. Here complexity is understood as inclusion of the DM as inseparable part of the complex system and as inclusion of the DM in the model description. The focus is analytical inclusion of the decision maker in the modeling and in the main objective function. Following from this, the orientation of the approach is toward the branch of the Model driven decision making in the taxonomy created by Daniel Power (Power, 2002). A model-driven decision making emphasizes access to and manipulation of a statistical, financial, optimization or simulation model. Model-driven decision making uses data and parameters provided by technologists to assist the DM in analyzing a situation.

Human thinking and preferences have qualitative nature which makes the problems in the domain of the complex systems with human participation to be considered as qualitative, i.e. difficult for analytical description. People's preferences contain characteristics of subjective and probabilistic uncertainty. This makes the mathematical incorporation of human preferences in complex systems difficult. Possible approach for resolving these problems is the stochastic approximation (Aizerman et al., 1970; Kivinen et al., 2004; Pavlov & Andreev, 2013). The uncertainty of the subjective preferences could be viewed as a noise which can be eliminated as is typical for stochastic approximation. A main requirement of the stochastic assessment is the analytical presentation of the qualitative nature of the human's preferences and notions (Keeney & Raiffa, 1993).

The main assumption in each management or control decision is that the values of the subject making the decision are the guiding force and as such they are the main moment in supporting the decisions (Keeney, 1988). In complex system with human participation the DM's values are implicitly and heuristically included. This means that there is no explicit objective function to allow for flexible behavior of the decision maker when forming the decisions. Such objective value function allows for quantitative analysis and removal of logical inconsistencies and errors (Castagne et al., 2009; Collopy & Hollingsworth, 2009). Value driven design can be defined as a development paradigm, in which required human value considerations are engineered into best practices, activities and management (Collopy, 2009). Value-driven control design enables design optimization by providing designers with an objective function. The value based presentation of objective function includes all the important attributes of a system being designed, and outputs a score (Hall & Davis, 2007; Castagne et al., 2009). At the whole system level, the objective function which performs this assessment of value is called a value model.

The main focus of the paper is the productive merger of mathematical exactness with the

empirical uncertainty in the human notions. A mathematical methodology that is useful for dealing with the uncertainty of human behavior in complex problems and mathematical description of the complex system "technologist-process" is presented here. The described approach permits representation of the individual's preferences as value/utility function, evaluated as machine learning and inclusion of this function in the value model as objective function.

BACKGROUND

In this approach the flexibility and the diversity of the Potential functions method (stochastic programming) and its conjunction with the Utility theory when the complex system is described analytically is demonstrated. The value/utility analytical descriptions have been built in agreement with the attitude of the technologist (or of the DM) toward the dynamical process. Using this approach, factors such as ecology, financial perspective and social effect can be taken into account. They are included in the DM's preferences via the DM's attitude towards them.

The first and the most important effect is the possibility for analytical description of such complex systems. The second effect is the introduction of iterativity in the process of the control design as it is used naturally in computer and analytical mathematical techniques. The third effect is that the process of training can be reversed towards the DM with the aim of additional analysis and corrections.

The approach is demonstrated via growth rate control design based on Monod-Wang kinetic model and its equivalent Brunovsky normal form. The specific growth rate of the fed-batch biotechnological processes determines the nominal biotechnological conditions (Neeleman, 2002). The complexity of the biotechnological cultivation process makes difficult the determination of the "*best*" process parameters. The incomplete information is compensated by the use of imprecise

human estimations. Our experience is that the human estimation of the parameters of a cultivation process contains uncertainty in the range from 10% to 30%. The algorithmic approach permits exact mathematical evaluation of the optimal specific growth rate of the fed-batch cultivation process according to the DM point of view even though the expert thinking is qualitative and pierced by uncertainty. The DM's utility function could be used as objective function for optimal control. Thus we achieve totally analytical mathematical description of the complex system "Technologist-biotechnological process."

Value and Utility Functions

We begin with the simplest case, the value functions (Fishburn, 1970; Keeney & Raiffa, 1993). Let $\mathbf{X}$ be the set of alternatives ($\mathbf{X} \subseteq \mathbf{R}^m$). A "value" function is a function $u^*(.)$ for which it is fulfilled: $((x, y) \in \mathbf{X}^2, x \subseteq y) \Leftrightarrow (u^*(x) > u^*(y))$.

The DM's preferences over $\mathbf{X}$ are expressed by ($\succ$). A value function gives us only the possibilities for determination of the maximum or minimum of a solution. Mathematical expectations with value functions are not possible.

The description of a utility function is more difficult. Let $\mathbf{X}$ be a set of alternatives and $\mathbf{P}$ is a subset of discrete probability distributions over $\mathbf{X}$. A utility function is any function $u(.)$ for which it is fulfilled: $(p \succ q, (p,q) \in \mathbf{P}^2) \Leftrightarrow ((\int u(.)dp > \int u(.)dq), p \in \mathbf{P}, q \in \mathbf{P}).$

According to Von Neumann the above formula means that the mathematical expectation of $u(.)$ is a quantitative measure in the interval scale with regard to the DM's preferences for probability distributions $\mathbf{P}$ over $\mathbf{X}$ (Fishburn, 1970; Keeney, & Raiffa, 1993). The DM's preferences over $\mathbf{P}$, including those over $\mathbf{X}$, ($\mathbf{X} \subseteq \mathbf{P}$) are expressed by($\succ$). The "indifference" relation ($\approx$) is defined by $((x \approx y) \Leftrightarrow \neg((x \succ y) \vee (x \succ y)))$. It is well known that the existence of a utility function $u(.)$ over $\mathbf{X}$ determines the "preference" relation ($\approx$) as a negatively transitive and asymmetric one (Fishburn, 1970):

Related Content

Big Data Technologies and Analytics: A Review of Emerging Solutions
Hoda Ahmed Abdelhafez (2014). *International Journal of Business Analytics (pp. 1-17).*
www.irma-international.org/article/big-data-technologies-and-analytics/115517

Forecasting Crude Oil Demand Using a Hybrid SVR and Markov Approach
Wei Xu, Jue Wangand Jian Ma (2010). *Business Intelligence in Economic Forecasting: Technologies and Techniques (pp. 235-247).*
www.irma-international.org/chapter/forecasting-crude-oil-demand-using/44257

Social Spider Algorithm for Training Artificial Neural Networks
Burak Gülmezand Sinem Kulluk (2019). *International Journal of Business Analytics (pp. 32-49).*
www.irma-international.org/article/social-spider-algorithm-for-training-artificial-neural-networks/238064

Business Intelligence 2.0: The eXtensible Markup Language as Strategic Enabler
Rubén A. Mendoza (2010). *International Journal of Business Intelligence Research (pp. 63-76).*
www.irma-international.org/article/business-intelligence-extensible-markup-language/47196

Impact of Credit Financing on the Ordering Policy for Imperfect Quality Items With Learning and Shortages
Mahesh Kumar Jayaswal, Isha Sangaland Mandeep Mittal (2022). *International Journal of Business Analytics (pp. 1-18).*
www.irma-international.org/article/impact-of-credit-financing-on-the-ordering-policy-for-imperfect-quality-items-with-learning-and-shortages/304829