Analysis of Dynamic Models by Optimization (ADMO)

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Keywords: model analysis, optimization, policy optimization, sensitivity, eigenvalue, pathway, yeast-alcohol, funnels

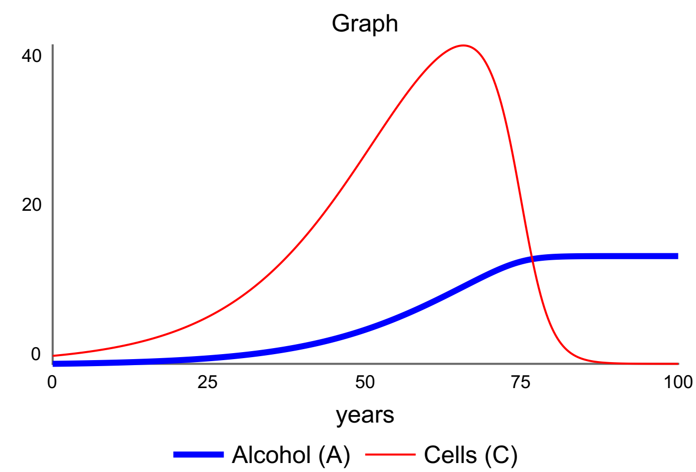
In management and politics, good policymaking relies on a proper understanding of the underlying system. Hence, analysts must be able to give understandable and correct explanations of how policies work using the most appropriate models of the system. Often, such models are non-linear and dynamically complex. Since such models are hard to understand, analysts can benefit from formal tools for policy analysis. In recent years, several methods have been developed and tested, notably loop eigenvalue elasticity analysis (LEEA) (Güneralp 2006; Saleh et al. 2010; Naumov and Oliva 2018) and pathway participation metrics (PPM) (Mojtahedzadeh 2008). These methods analyze model structure and identify the feedback loops that are generating the observed behavior of the model over time. The methods have been tested extensively on different models in the past few years.

However, not all questions that policy makers find important can be answered through the lens of dominant dynamic structures. For example, consider a flow that is influenced by two stocks, one that is actively changing through a feedback loop, but is small, and another that is not changing, but is much larger. Then the loop dominance methods would prioritize the loop that contains the first stock, while the actual effect of that loop on the flow might be smaller than that of the second stock. Therefore, we need a tool that can explain phenomena of interest in terms of all elements of model structure, even if they are not changing dynamically.

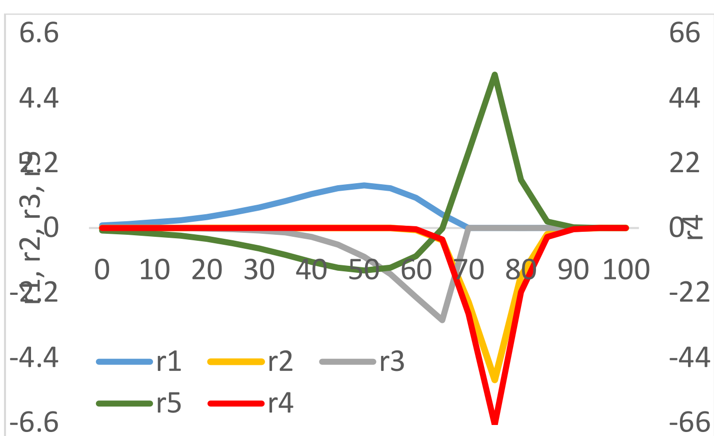
To do this we design an optimization method (ADMO) that can be easily implemented in existing simulation programs such as Powersim, Stella, and Vensim. The phenomenon of interest is quantified and optimized or minimized with respect to a number of "r-parameters" that are inserted in the causal links of the model. The optimization criterion is created such that for each r-parameter the cost increases as the r-parameter deviates from zero. The deviation from zero signals how important the link is for the phenomenon. The approach is similar to the ANTs method used for finding model vulnerabilities (Miller 1998).

After explaining the method in detail, we find analytical optimization results for isolated links from stocks to flows. This gives insights about what the inserted parameters reveal and about where they should be placed in chains of links from stocks to flows. Then we apply the method to the nonlinear and dynamic yeast-alcohol model. The phenomenon we consider and maximize is the amount of alcohol at the end of the simulation, see the simulated behavior below.

We analyze the model with ADMO. The figure below shows how the r-values develop over time. Parameter $r1$ shows that in the first minutes the effect of yeast cells on births of new yeast cells is important. The effect of cells on the generation of alcohol $r5$ is similarly important for the end value of alcohol, however, in the opposite direction. Note that negative values of $r5$ in the first minutes mean that early alcohol generation will eventually limit the cell population; see the later negative effects of alcohol on births r3 and on deaths r4. After 65 minutes, generation of alcohol $r5$ has the expected and desired positive effect on the end value of alcohol. Different from LEEA and PPM, the minor death loop of cells, $r2$, is of much less importance than the effect of alcohol on cell deaths, $r4$ (note the larger scale for $r4$). The effect of alcohol on deaths is important because it has a strong influence on the cell population that produces alcohol. LEEA and PPM neglect the effect of alcohol because the alcohol level stagnates towards the end, so there is no longer activity around this major death loop.



Finally, we discuss the difference between analyzing explanations of phenomena and finding optimal policies. A model with two funnels is used to illustrate. ADMO explains how the current policy produce a problematic overshoot (phenomenon) and indicates what information alternative feedback policies should consider. This helps limit the number of variables to consider when performing policy optimization and makes the process of policy optimization more efficient. This is particularly important in large models where many variables could be considered in alternative feedback policies. ADMO also indicates what design parameters should be reconsidered and optimized.



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