Optimized Behavioral Interventions: What Does Control Systems Engineering Have to Offer?

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CSEL Control Systems Engineering Laboratory

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ASU Ira A. Fulton school of engineering ARIZONA STATE UNIVERSITY

About this talk

- Goal is to discuss how control systems engineering can inform the design and implementation of time-varying adaptive behavioral interventions.
- Talk will have some tutorial flavor, but will not be a comprehensive survey.
- Emphasis will be given to the *connections* between behavioral health, methodology, and engineering, and the opportunities (and challenges) that these present to the behavioral scientist, the methodologist, and the engineer.

Outline

- What is meant by control systems engineering?
- How can these concepts improve behavioral interventions?
  - Hypothetical time-varying adaptive intervention (inspired by the *Fast Track* program) as a control system problem.
  - Description and application of Model Predictive Control.
- Relating theory to control engineering modeling: Theory of Planned Behavior in a weight loss intervention.
- Summary and conclusions; looking to the future.

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Current Projects in Behavioral Health

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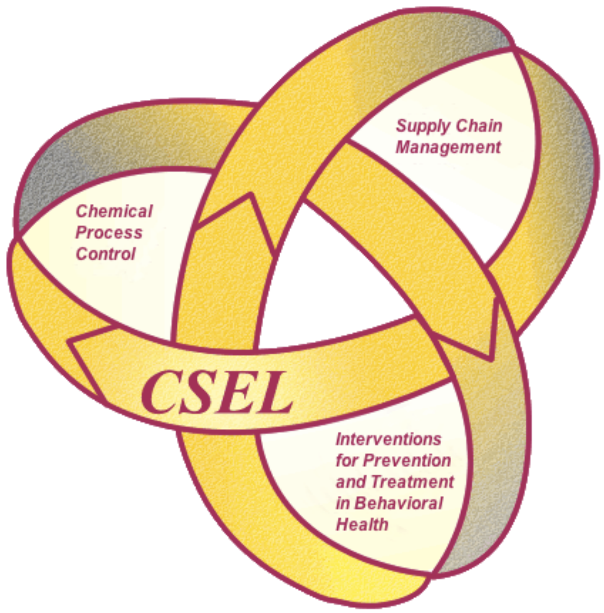
- K25DA021173*, "Control engineering approaches to adaptive interventions for fighting drug abuse," Mentors: L.M. Collins (Penn State) and S.A. Murphy (Michigan).
- R21DA024266*, "Dynamical systems and related engineering approaches to improving behavioral interventions," *NIH Roadmap Initiative Award on Facilitating Interdisciplinary Research Via Methodological and Technological Innovation in the Behavioral and Social Sciences,* with L.M. Collins, Penn State, co-PI.

Funding received from NIDA (National Institute on Drug Abuse) and OBSSR (Office of Behavioral and Social Sciences Research) is gratefully acknowledged.

Our Logo (in more detail)...



http://csel.asu.edu/health

Similarities Between Behavioral Scientists and Control Engineers

- Behavioral scientists are interested in developing and delivering effective interventions that:
  - demonstrate high levels of adherence.
  - display uniformity and reproducibility despite heterogeneity of the target population, and inherent variability associated with delivery of the intervention,
  - are cost-effective in nature.

All these goals are compatible with the objectives of control systems engineering...

Control Systems Engineering

- The field that relies on dynamical models to develop algorithms for adjusting system variables so that their behavior over time is transformed from *undesirable* to *desirable*.

- Control engineering plays an important part in many everyday life activities. Some examples of control systems engineering applications include:
  - Cruise control and climate control in automobiles,
  - The "sensor reheat" feature in microwave ovens,
  - Home heating and cooling,
  - The insulin pump for Type-I diabetics,
  - "Fly-by-wire" systems in high-performance aircraft,
  - Homeostasis,
  - Many, many, more...

Control Systems Engineering (Continued)

Control systems engineers strive to improve system operation by "closing the loop":

- <u>Open-loop</u>: refers to system behavior without a controller or decision rules (i.e., MANUAL operation).

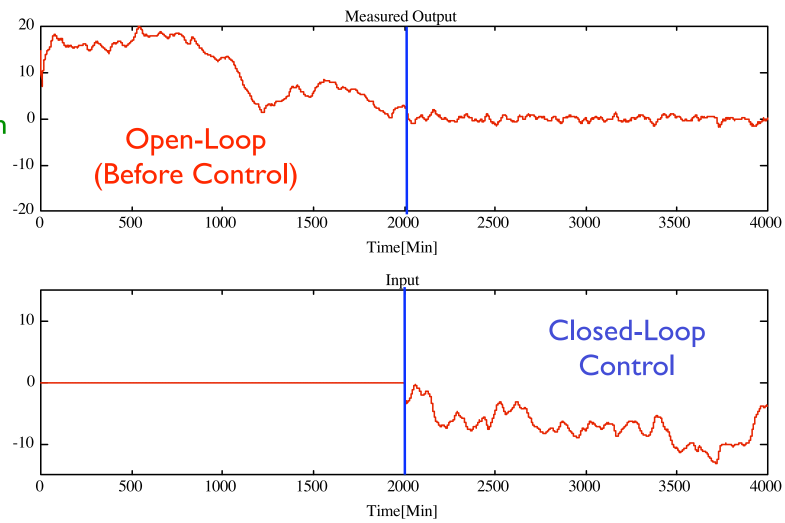
- <u>Closed-loop</u>: refers to system behavior once a controller or decision rule is implemented (i.e., AUTOmatic operation).

  A well-tuned control system will effectively *transfer variability* from an expensive system resource to a less expensive one.

From Open-Loop Operation to Closed-Loop Control (Stochastic Viewpoint)

Controlled Variable Deviation
(e.g., Temperature)

Manipulated Variable Deviation
(e.g., Flowrate)



The transfer of variance from an expensive resource to a cheaper one is one of the major benefits of control systems engineering

Control Engineering Concepts Are Not New to Psychology...

• Carver C.S. and M.F. Scheier. <u>On the self-regulation of behavior</u>. New York: Cambridge University Press; 1998.

• Hyland, M.E., "Control theory interpretation of psychological mechanisms of depression: comparison and integration of several theories," *Psychological Bulletin*, Vol. 102, No. 1, pgs. 109-121, 1987.

• Molenaar, P.C.M., "Dynamic assessment and adaptive optimization of the psychotherapeutic process," *Behavioral Assessment,* Vol. 9, pgs. 389-416, 1987.

• Molenaar, P.C.M., "Note on optimization of individual psychotherapeutic processes," *Journal of Mathematical Psychology*, Vol. 54, pgs. 208-213, 2010.

Basic Components of Adaptive Interventions

(Collins, Murphy, and Bierman, *Prevention Science*, **5**, No. 3, 2004)

- The assignment of a particular dosage and/or type of treatment is based on the individual's values on variables that are expected to moderate the effect of the treatment component; these are known as *tailoring variables*.
- In a *time-varying* adaptive intervention, the tailoring variable is assessed periodically, so the intervention is adjusted on an on-going basis.
- *Decision rules* translate current and previous values of tailoring variables into choice(s) of treatment and their appropriate dosage.

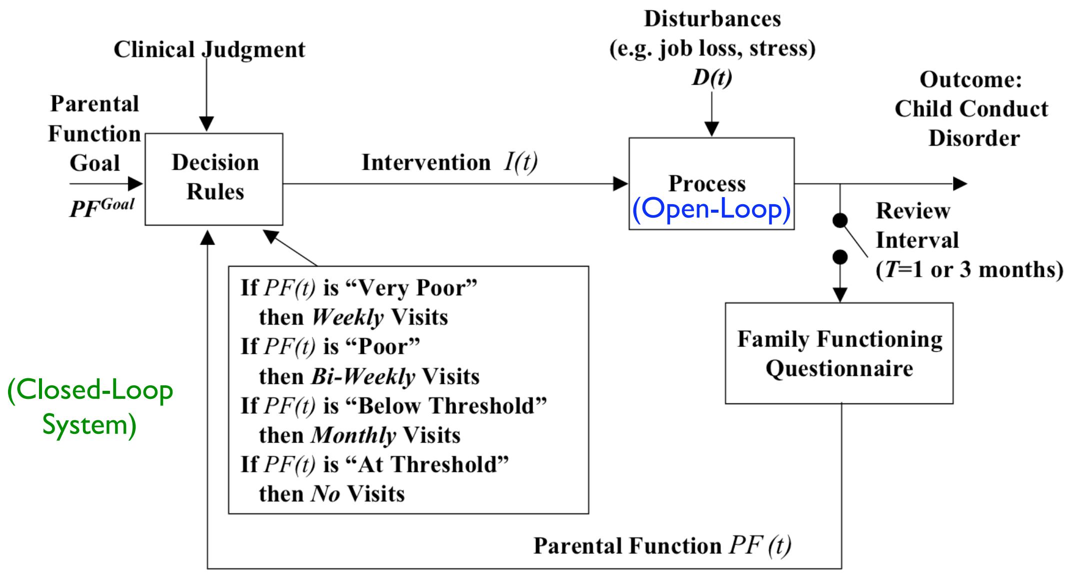
Adaptive Intervention Simulation

(inspired by the *Fast Track* Program, Conduct Problems Prevention Research Group)

- A multi-year program designed to prevent conduct disorder in at-risk children.
- Frequency of home-based counseling visits assigned quarterly to families over a three-year period, based on an assessed level of parental functioning.
- Parental function (the tailoring variable) is used to determine the frequency of home visits (the intervention dosage) according to the following decision rules:
  - If parental function is "very poor" then the intervention dosage should correspond to weekly home visits,
  - If parental function is "poor" then the intervention dosage should correspond to bi-weekly home visits,
  - If parental function is "below threshold" then the intervention dosage should correspond to monthly home visits,
  - If parental function is "at threshold" then the intervention dosage should correspond to no home visits.

Parental Function Feedback Loop *Block Diagram**

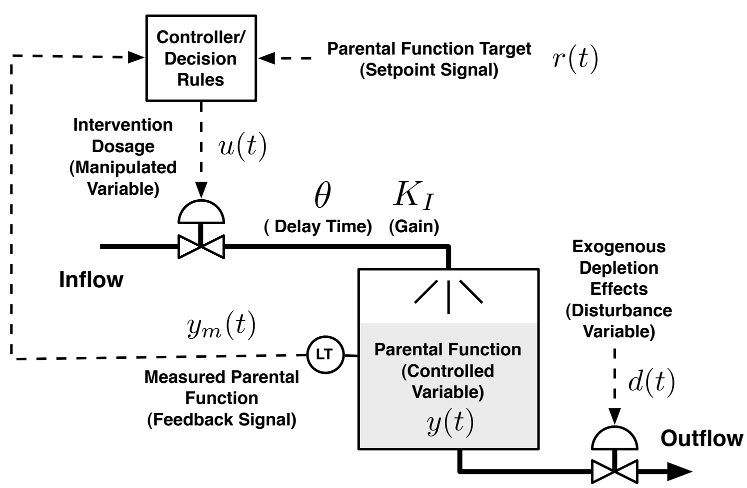
(to decide on home visits for families with at-risk children)



From Rivera, D.E., M.D. Pew, and L.M. Collins, "Using engineering control principles to inform the design of adaptive interventions: a conceptual introduction," *Drug and Alcohol Dependence*, Special Issue on Adaptive Treatment Strategies, Vol. 88, Supplement 2, May 2007, Pages S31-S40.

Parental Function - Home Visits Adaptive Intervention as a Production-Inventory Control System

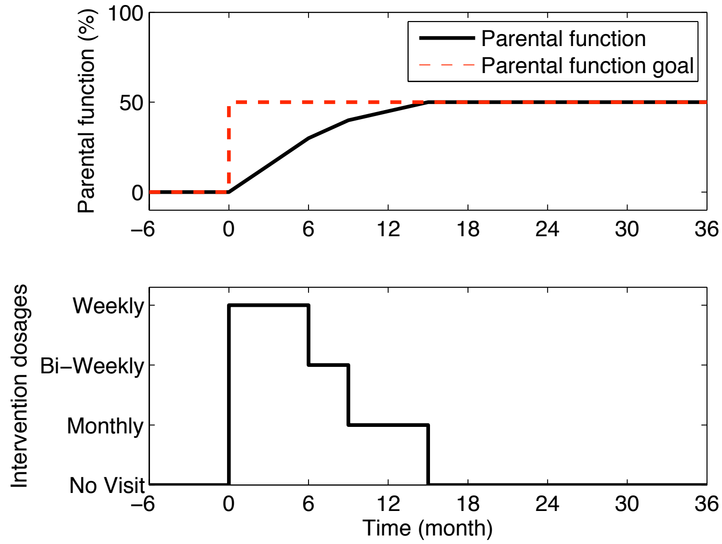
(Rivera, Pew, and Collins, "Using engineering control principles to inform the design of adaptive interventions," *Drug and Alcohol Dependence*, Vol. 88, Suppl. 2, May 2007, Pages S31-S40)



$$y(t+1) = y(t) + K_I\ u(t-\theta) - d(t)$$

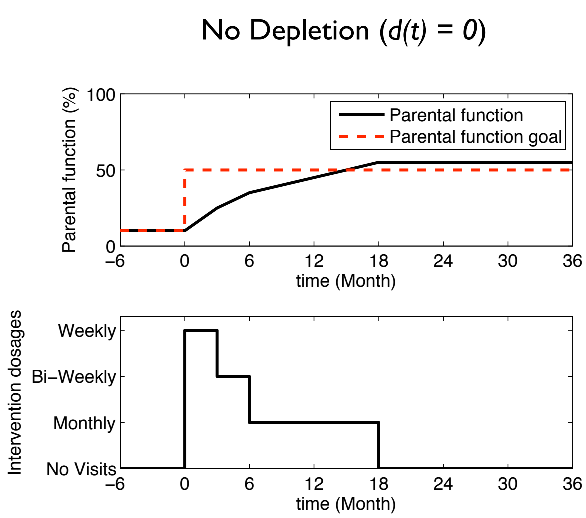
Parental function *y(t)* is built up by providing an intervention *u(t)* (frequency of home visits), that is potentially subject to delay, and is depleted by potentially multiple disturbances (adding up to *d(t)*).

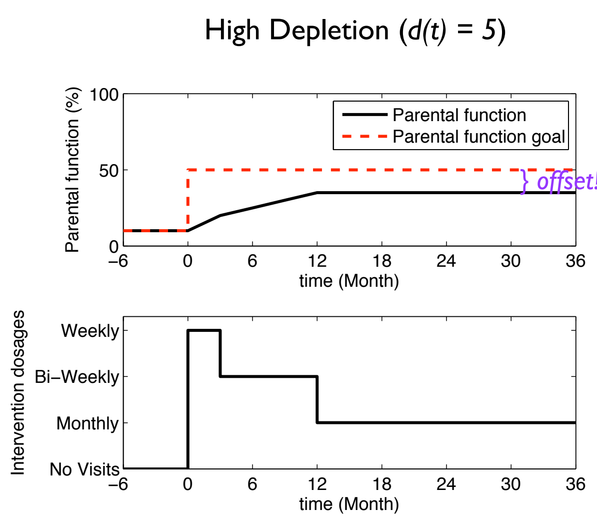
Parental Function - Counselor Home Visits Adaptive Intervention Single Participant Family Illustration



- The assigned dosage (frequency of counseling visits) decreases as the tailoring variable (parental function) increases, as prescribed by the decision rules.

Simple "IF-THEN" Rules May Not Be Optimal



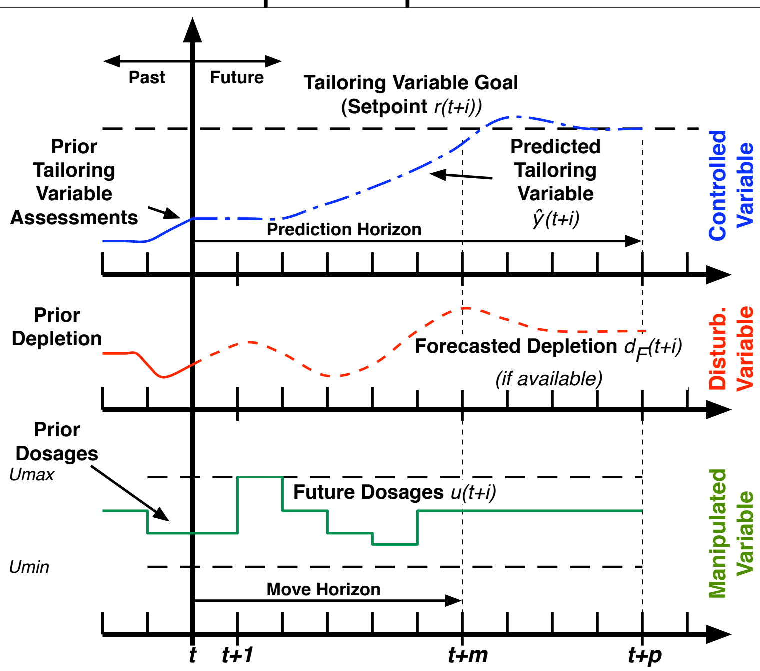


Single participant family scenario. *Offset* (where parental function fails to reach a desired goal at the end of the intervention) occurs when high depletion (representing a large magnitude disturbance) is present.

Model Predictive Control (MPC)

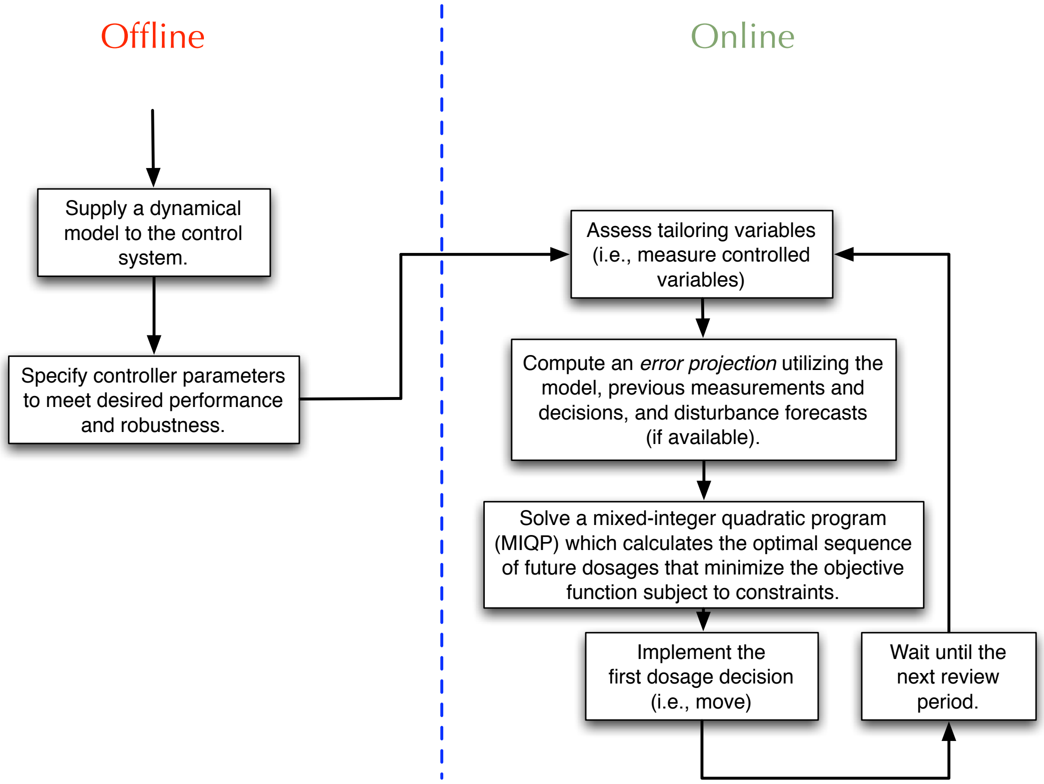
- Control engineering technology widely used in many industrial applications (from chemical mfg to automotive and aerospace).
- As an *optimization technology*, MPC can minimize (or maximize) an objective function that represents a suitable metric of intervention performance.
- As a *control system*, MPC accomplishes feedback (and feedforward action) in the presence of model error, measurement unreliability, and disturbances that may affect the intervention.
- Three major steps in MPC:
  - *Prediction* of intervention outcomes at time instants in the future (i.e., the prediction horizon) based on a model,
  - *Optimization* of a sequence of future dosage decisions through minimizing (or maximizing) an objective function,
  - Receding horizon strategy.

Model Predictive Control Conceptual Representation



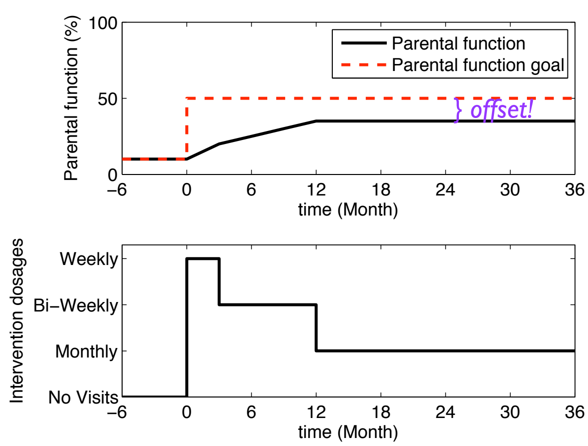
$$\min_{\Delta u(t)\ldots\Delta u(t+m-1)} J = \overbrace{\sum_{i=1}^{p} Q_e(i)(\hat{y}(t+i) - r(t+i))^2}^{\text{Take Tailoring Variables to Goal}} + \overbrace{\sum_{i=1}^{m} Q_{\Delta u}(i)(\Delta u(t+i-1))^2}^{\text{Penalize Changes in the Intervention Dosages}}$$

Model Predictive Control Flowchart

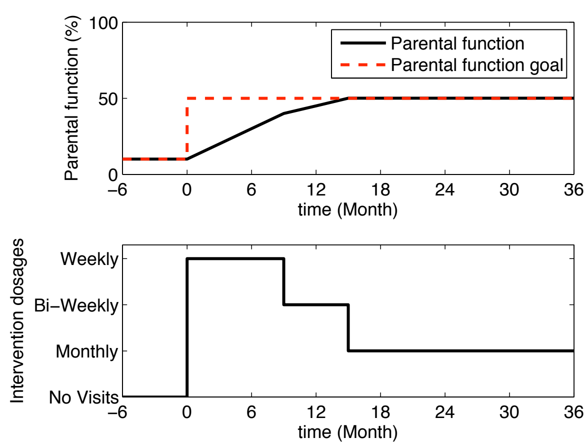


Controller/Decision Rule Comparison, Scenario 1
High Depletion Rate ($d(t) = 5$)

"IF-THEN" rules



Model Predictive Control
($Q_e = 1, Q_{du} = 0.05, p = 30, m = 10$)

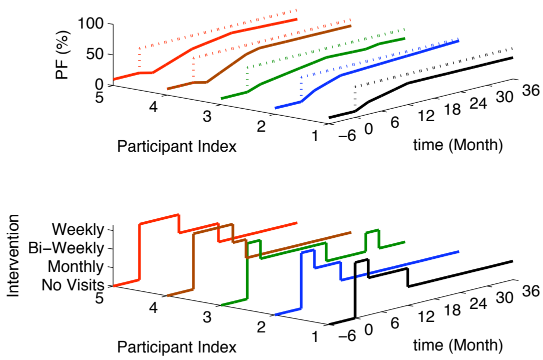


36 month intervention reviewed at quarterly intervals. Offset problem is eliminated in the MPC controller through judicious assignment of intervention dosages during the course of the intervention.

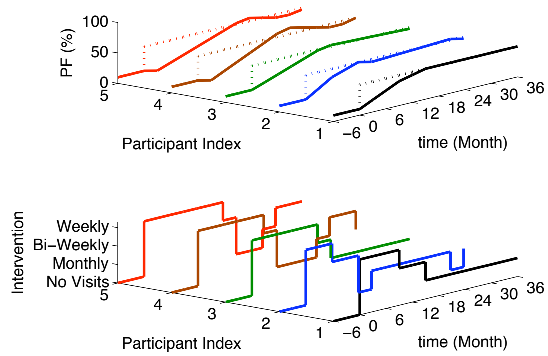
IF-THEN vs. MPC Comparison (Robustness Analysis)

- The system response of five participant families, each characterized by its own dynamical model, is evaluated using a controller tuned on the basis of an average ("nominal") effect.

"IF-THEN" Decision Rules



MPC Control
(Q_e = 1, Q_{du} = 0.05, p = 30, m = 10)



- The MPC controller individually assigns the proper intervention dosages to each participant family, leading to no offset and more consistent outcomes. This is achieved at the expense of greater variability in the intervention dosages.

Simulation Cases

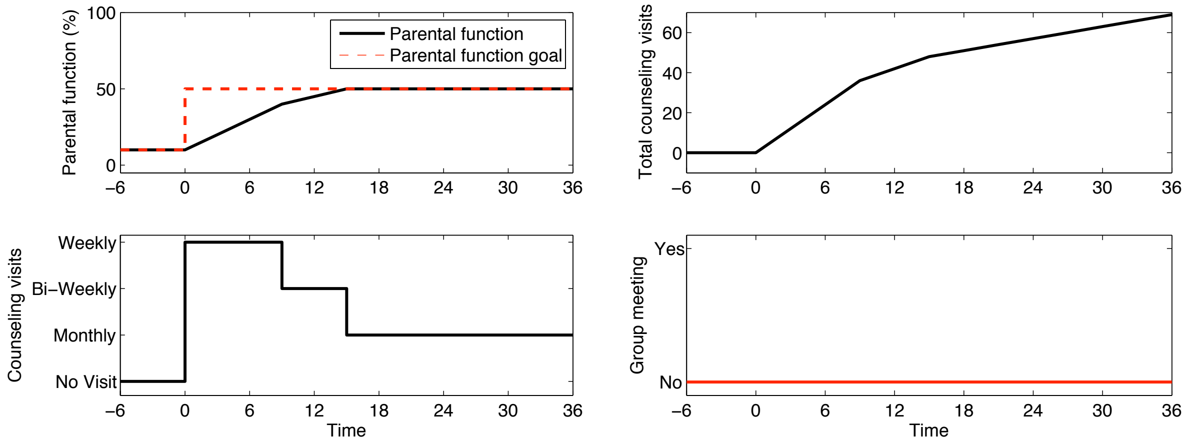
- Scenario 1: Comparison with simple "IF-THEN" rules.
- Scenario 2: Constrained, augmented operation.

Total number of counseling visits constrained to an upper limit; group counseling may be offered when in-home visit limit is reached.

- Scenario 2(a):
  - » Unlimited counseling visits, no group meeting available.
- Scenario 2(b) :
  - » Overall dosage limited to a maximum of 48 in-home counseling visits;
  - » no group meeting available.
- Scenario 2(c):
  - » Overall dosage limited to a maximum of 48 in-home counseling visits;
  - » Group counseling available when in-home visit limitation is reached.

Scenario 2(a)

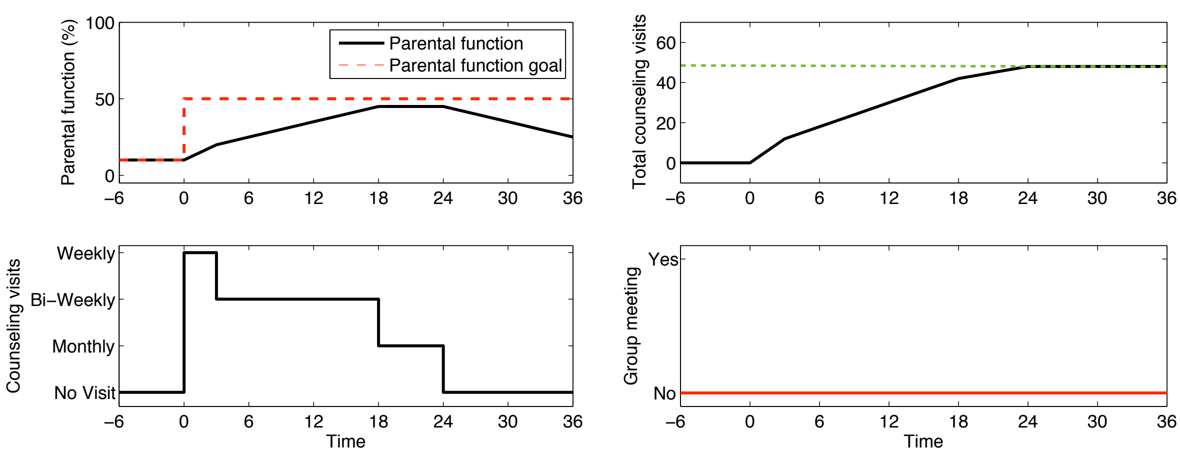
(No limit on number of counseling visits; no group meeting offered)



- 69 total counseling visits required in this unconstrained scenario to achieve the parental function goal *without* offset.

Scenario 2(b)

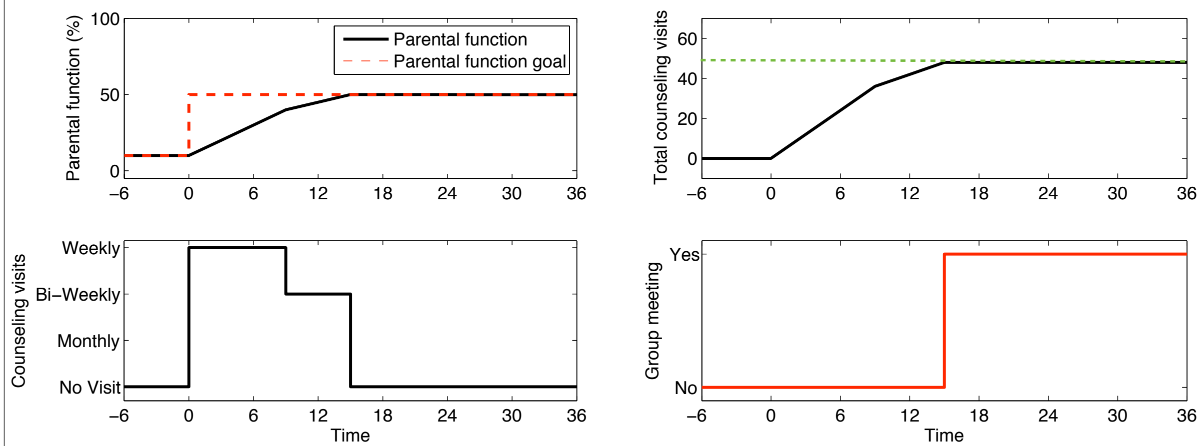
(Counseling visits limited to 48 *(total)*; no group meeting offered)



- The dosage constraint places a fundamental limit on the effectiveness of the intervention. The controller does "the best it can" (for the given objective function parameters), within these restrictions.

Scenario 2(c)

(Counseling visits limited to 48 *(total)*; group meeting available)



- MPC adapts the intervention to meet the outcome goal, properly sequencing the additional intervention component (once the counseling visits limit is reached).

Some Challenges

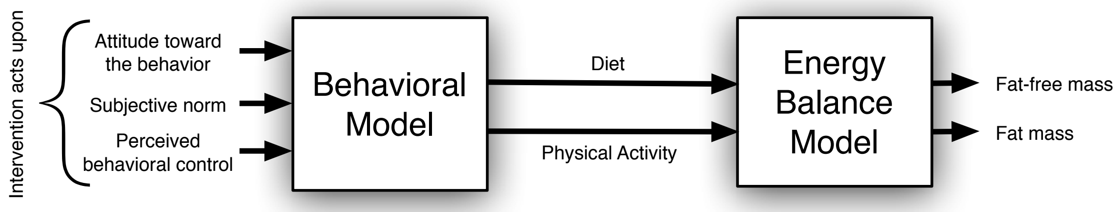
- Dynamic modeling from intensive longitudinal data using ideas from system identification (engineering) and functional data analysis (statistics).

- Developing novel (and practical) experimental designs within the vast, challenging domain of behavioral health.

- Issues with controller tuning (which impact modeling); resolving the nomothetic versus idiographic debate.

- Application areas (with L.M. Collins, R21 Roadmap Project):
  - Low-dose naltrexone for fibromyalgia (Jarred Younger, Stanford University).
  - Weight loss interventions; prevention of excessive gestational weight gain (D. Downs, J. Savage and L. Birch, Penn State; D. Thomas, Montclair State)
  - Dynamical systems modeling of smoking behavior and cessation (with M. Piper, T. Baker, M. Fiore, UW-Center for Tobacco Research and Intervention)

Conceptual Model for Weight Change Interventions

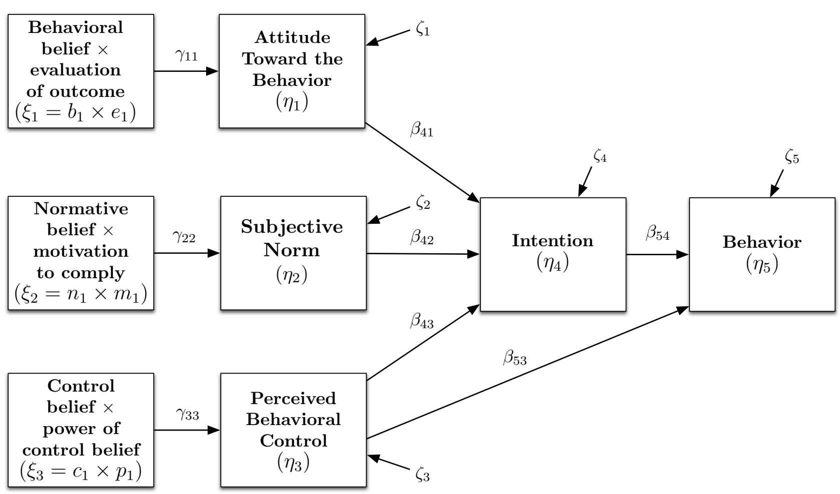


The dynamical model consists of a system of integrated differential equations describing:

- Physiology (energy balance),
- Behavior change (Theory of Planned Behavior).

Navarro-Barrientos, J.E., D.E. Rivera, and L.M. Collins, "A dynamical systems model for understanding behavioral interventions for weight loss," *2010 International Conference on Social Computing, Behavioral Modeling, and Prediction* (SBP 2010), Springer.

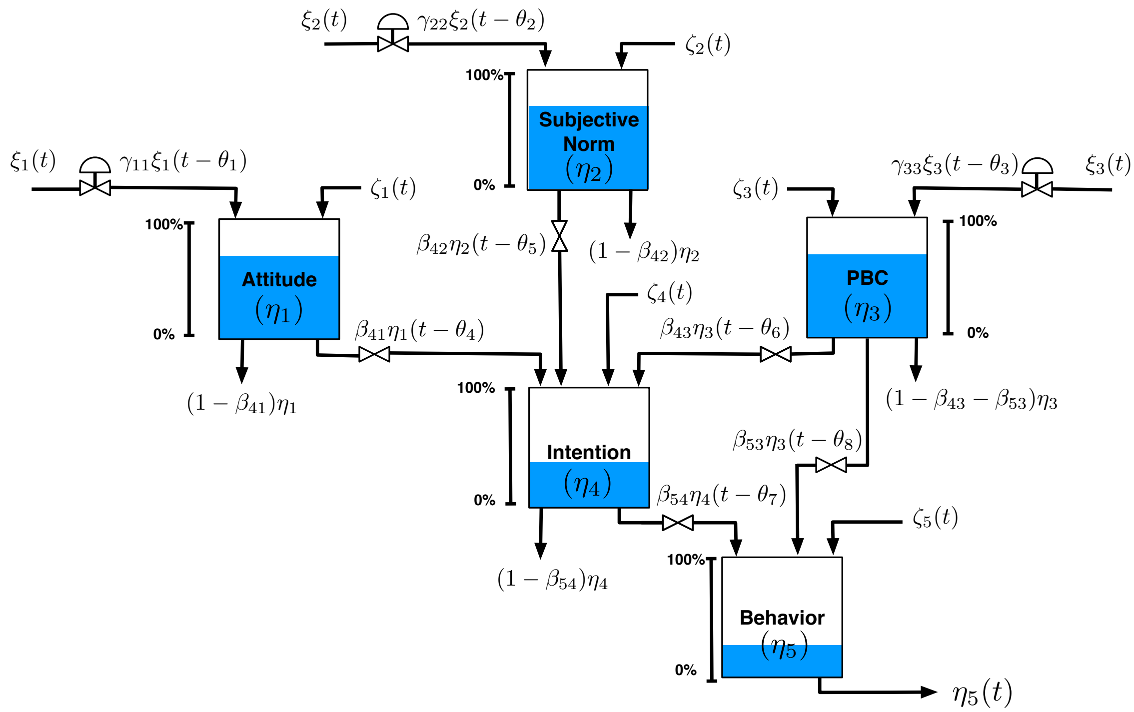
Path Diagram for the Theory of Planned Behavior



$$\eta = \mathbf{B}\,\eta + \mathbf{\Gamma}\,\xi + \zeta$$

$$\begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \\ \eta_5 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ \beta_{41} & \beta_{42} & \beta_{43} & 0 & 0 \\ 0 & 0 & \beta_{53} & \beta_{54} & 0 \end{bmatrix} \begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \\ \eta_5 \end{bmatrix} + \begin{bmatrix} \gamma_{11} & 0 & 0 \\ 0 & \gamma_{22} & 0 \\ 0 & 0 & \gamma_{33} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \zeta_3 \\ \zeta_4 \\ \zeta_5 \end{bmatrix}$$

Fluid Analogy for the Theory of Planned Behavior



Dynamic TPB Model

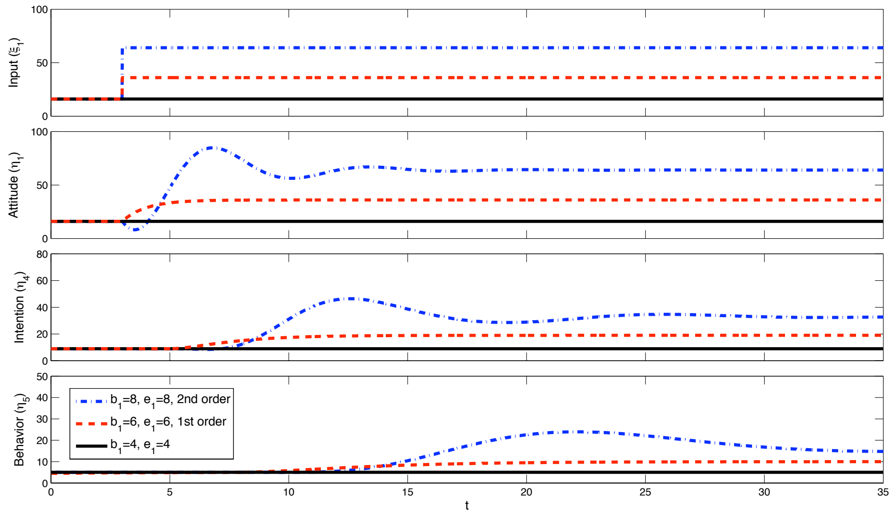
The conservation principle (Accumulation = Inflow − Outflow) leads to the following system of differential equations:

$$
\begin{aligned}
\tau_1 \frac{d\eta_1}{dt} &= \gamma_{11}\xi_1(t-\theta_1) - \eta_1(t) + \zeta_1(t) \\
\tau_2 \frac{d\eta_2}{dt} &= \gamma_{22}\xi_2(t-\theta_2) - \eta_2(t) + \zeta_2(t) \\
\tau_3 \frac{d\eta_3}{dt} &= \gamma_{33}\xi_3(t-\theta_3) - \eta_3(t) + \zeta_3(t) \\
\tau_4 \frac{d\eta_4}{dt} &= \beta_{41}\eta_1(t-\theta_4) + \beta_{42}\eta_2(t-\theta_5) + \beta_{43}\eta_3(t-\theta_6) - \eta_4(t) + \zeta_4(t) \\
\tau_5 \frac{d\eta_5}{dt} &= \beta_{54}\eta_4(t-\theta_7) + \beta_{53}\eta_3(t-\theta_8) - \eta_5(t) + \zeta_5(t),
\end{aligned}
$$

where:
$\tau_1, \cdots, \tau_5$ are time constants,
$\eta_1, \cdots, \eta_5$ are the inventories,
$\xi_1(t) = b_1(t)e_1(t)$, $\xi_2(t) = n_1(t)m_1(t)$, $\xi_3(t) = c_1(t)p_1(t)$,
$\gamma_{11}, \cdots, \gamma_{33}$ are the inflow resistances,
$\beta_{41}, \cdots, \beta_{54}$ are the outflow resistances,
$\theta_1, \cdots, \theta_7$ are time delays and $\zeta_1, \cdots, \zeta_5$ are disturbances.

Dynamic TPB Model: simulation results

System response for various step change increases in strength of beliefs to attitude:

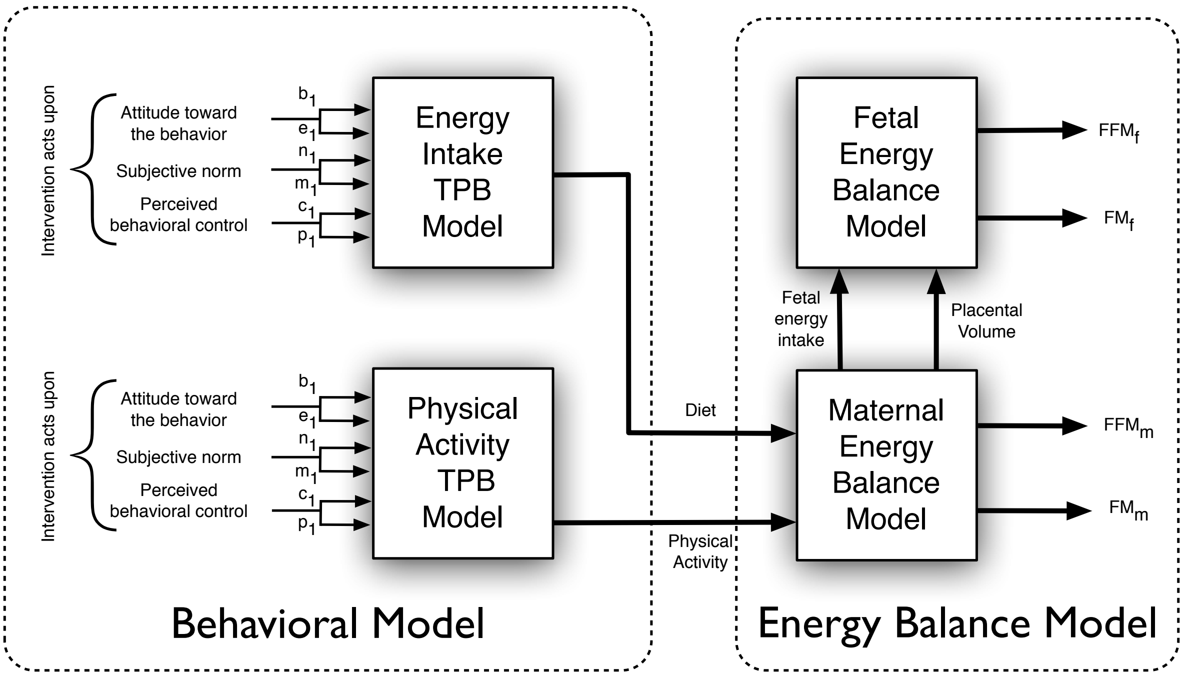


$\xi_1 = b_1 \times e_1$:	Model parameters:
(solid) $b_1 = 4,\ e_1 = 4$	$\theta_1 = \cdots \theta_3 = 0,\ \theta_4 = \cdots \theta_7 = 2$
(dashed) $b_1 = 6,\ e_1 = 6$	$\tau_1 = \cdots \tau_3 = 1,\ \tau_4 = 2,\ \tau_5 = 4$
(dot-dashed) $b_1 = 8,\ e_1 = 8$	$\gamma_{ij} = 1,\ \beta_{ij} = 0.5,\ \zeta_i = 0$

Dynamical TPB Model Summary

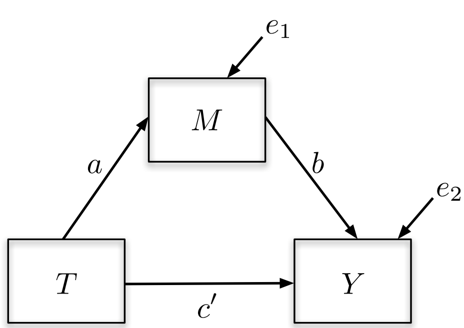
- At steady-state, the dynamical model corresponds exactly to the TPB structural equation model (SEM),
- Additional model parameters (time constants, delays, and damping coefficients) represent transient behavior in a manner fully consistent with dynamical systems theory,
- Parameter estimation from data can be accomplished by:
  - system identification (engineering)
  - functional data analysis (statistics).

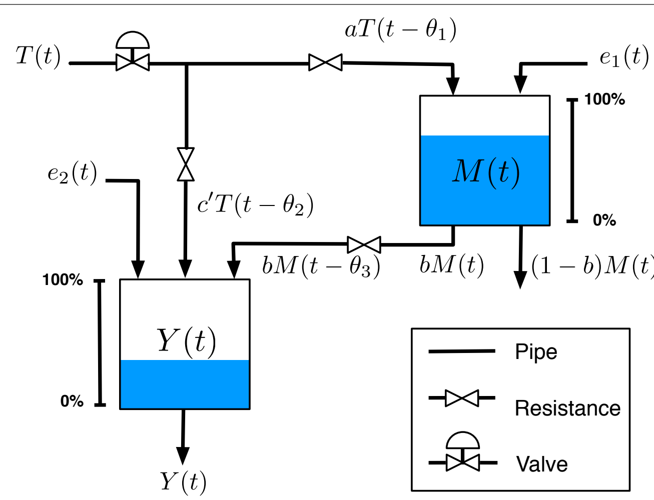
Conceptual Model for Gestational Weight Gain Interventions



Fluid Analogy for Mediation Analysis

Path Diagram:





$$\tau_1 \frac{dM}{dt} = a\,T(t-\theta_1) - M(t) + e_1(t)$$

$$\tau_2 \frac{dY}{dt} = c'\,T(t-\theta_2) + b\,M(t-\theta_3) - Y(t) + e_2(t).$$

Time constant (τ) and delay (θ) variables are essential features in this dynamic model representation for mediation. Aspects of moderation and confounding phenomena can also be explained through a fluid analogy.

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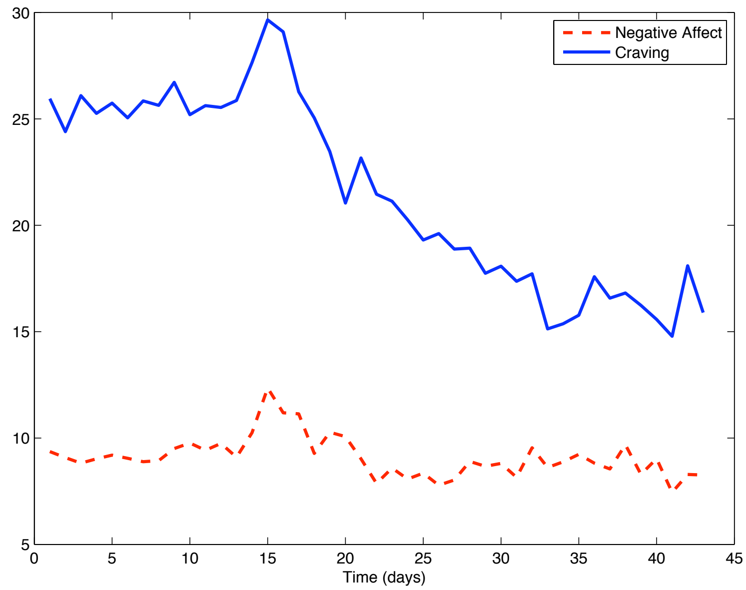
Smoking Cessation Intervention: Group Averages



- Following the quit date (day 15), dynamic responses are observed in craving (blue) and negative affect (red) for treatment group receiving drug and counseling.

Summary and Conclusions

- Adaptive behavioral interventions constitute dynamical systems that can be optimized by applying a control engineering perspective.
- Applying a control engineering requires intensive measurement and a recognition of the input/output nature of phenomena associated with behavioral interventions.
- A hypothetical adaptive intervention based on *Fast Track* has been evaluated using simple "IF-THEN" decision rules vs. an engineering-based Model Predictive Control decision algorithm.
- Fluid analogies from supply chain management have been useful as the basis for modeling adaptive interventions, and relating theory and SEM models to engineering control systems.
- A plethora of opportunities exist in applying systems approaches to behavioral interventions which include novel experimental design, formulation of optimal decision policies, and simulation.

Looking to the Future

We have considered the importance of *establishing connections* between prevention/behavioral health, methodology, and engineering. Some implications of this work (*not an exhaustive list*):

- Behavioral scientist: willingness to collect and work with intensive longitudinal data, reconfigure interventions to enable adaptation (i.e., systematically assess tailoring variables and allow dosage changes through the course of the intervention).
- Methodologist: develop expertise and familiarity with differential equations, dynamical input/output system models, and control theory.
- Control engineer: work with data sets that may be irregularly sampled, have missing entries, and involve multiple human participants. Understand experimental designs meaningful to problems in behavioral health. Examine and understand the nomothetic vs. idiographic methods debate.

Acknowledgments

- Linda M. Collins, Ph.D., The Methodology Center and Dept. of Human Development and Family Studies, Penn State University.
- Susan D. Murphy, Ph.D., Department of Statistics, Department of Psychiatry, and Institute for Social Research, Univ. of Michigan.
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Primary References

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- Rivera, D.E., M.D. Pew, L.M. Collins, and S.A. Murphy, "Engineering control approaches for the design and analysis of adaptive, time-varying interventions," Technical Report 05-73, The Methodology Center, Penn State University;

- Nandola, N. and D.E. Rivera, "A novel model predictive control formulation for hybrid systems with application to adaptive behavioral interventions," *Proceedings of the 2010 American Control Conference*, Baltimore, MD, June 30 - July 2, 2010.

- Navarro-Barrientos, J.E., D.E. Rivera, and L.M. Collins, "A dynamical systems model for understanding behavioral interventions for weight loss," *2010 International Conference on Social Computing, Behavioral Modeling, and Prediction (SBP 2010)*, March 29 - April 1, 2010; extended version in press to *Mathematical and Computer Modelling of Dynamical Systems*.

Additional References

- Some additional tutorial presentations that may be of interest:
  - Rivera, D.E., "Engineering control theory: can it impact adaptive interventions?" tutorial presentation at 2010 Society for Prevention Research workshop, June 1, 2010. Can be downloaded from http://csel.asu.edu/adaptiveintervention (select item 10).
  - Rivera, D.E., "A brief introduction to system identification," Penn State Methodology Center Brown Bag presentation, March 20, 2008. Can be downloaded from http://csel.asu.edu/controleducation (select item 10).
  - Rivera, D.E., "An introduction to mechanistic models and control theory," tutorial presentation at the SAMSI Summer 2007 Program on Challenges in Dynamic Treatment Regimes and Multistage Decision-Making, June 18 - 29, 2007. Can be downloaded from http://csel.asu.edu/controleducation (select item 9).
- A free web-based reference, written by two distinguished control engineers:
  - Åström, K. J. and R. M. Murray. **Feedback systems: an introduction for scientists and engineers**," http://www.cds.caltech.edu/~murray/amwiki.