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

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Behaviour Change Initiative Lecture Series
University College, London
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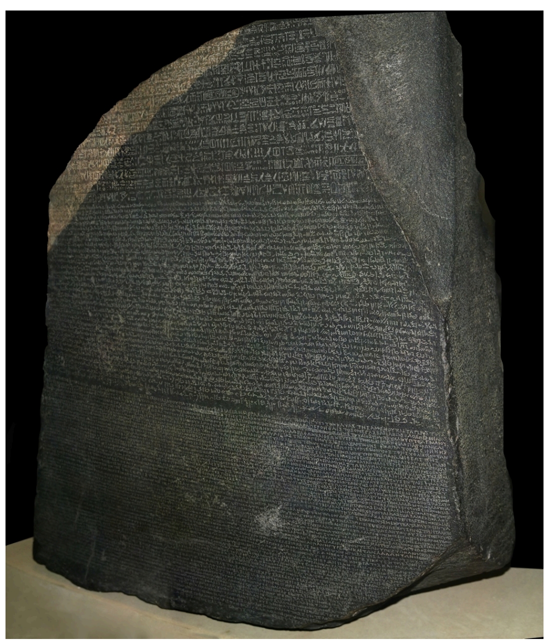
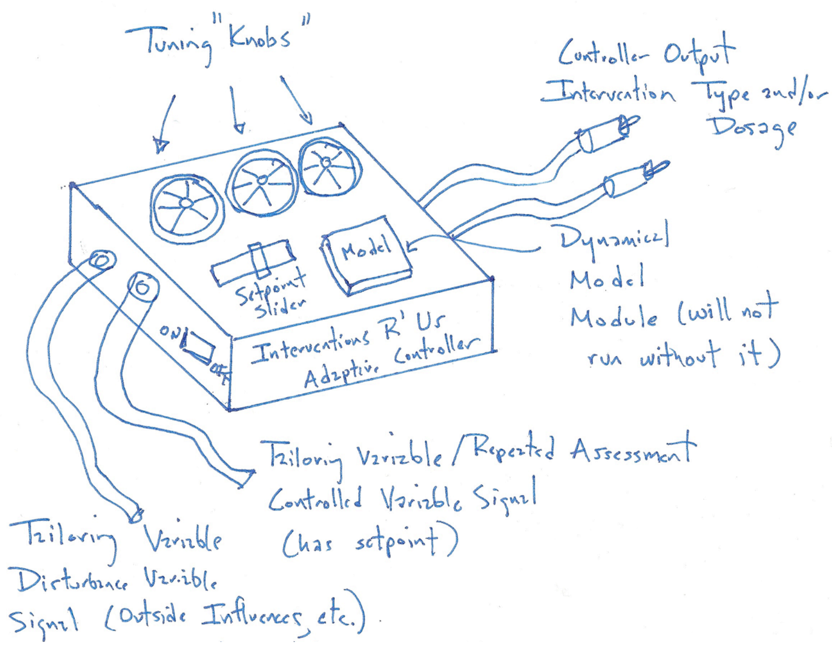
Discovering "Rosetta Stones"



Optimized Intervention "Box"
(*coming to a store near you...*)



- A "hardware" view to what is often perceived a "hidden" technology.

Presentation Outline

- What is meant by control systems engineering, and how can it improve behavioral interventions?
  - Hypothetical time-varying adaptive intervention (inspired by the *Fast Track* program) as a control system.
  - Application of Model Predictive Control (MPC).
- Some additional illustrations:
  - Prevention of excessive gestational weight gain,
  - Smoking cessation treatment using bupropion and counseling.
- Concluding remarks and acknowledgements.

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 :
  - Cruise control and climate control in automobiles,
  - The "sensor reheat" feature in microwave ovens,
  - Home heating and cooling,
  - The artificial pancreas for Type-I diabetics,
  - Fly-by-wire systems in high-performance aircraft,
  - Homeostasis

- Many other examples (including success stories and grand challenges) are presented in http://ieeecss.org/general/impact-control-technology

Open-Loop (MANual) vs. Closed-Loop (AUTOmatic) Control

- Control systems engineering aims at improving system operation by "closing the loop":

MANual AUTOmatic

Climate control in automobiles is one of many illustrations of closed-loop control that can be found in daily life.

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Gasoil Furnace Control System

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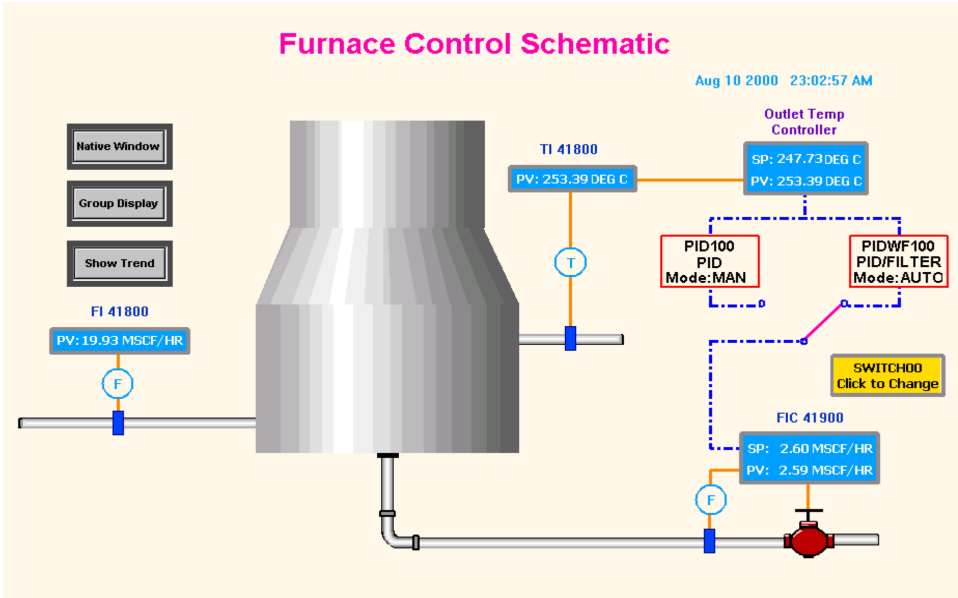

Objective: adjust fuel flow (manipulated var.) to keep gasoil outlet temperature at setpoint (controlled var.), despite variations in feed flow (disturbance var.).

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The "Shower" Problem

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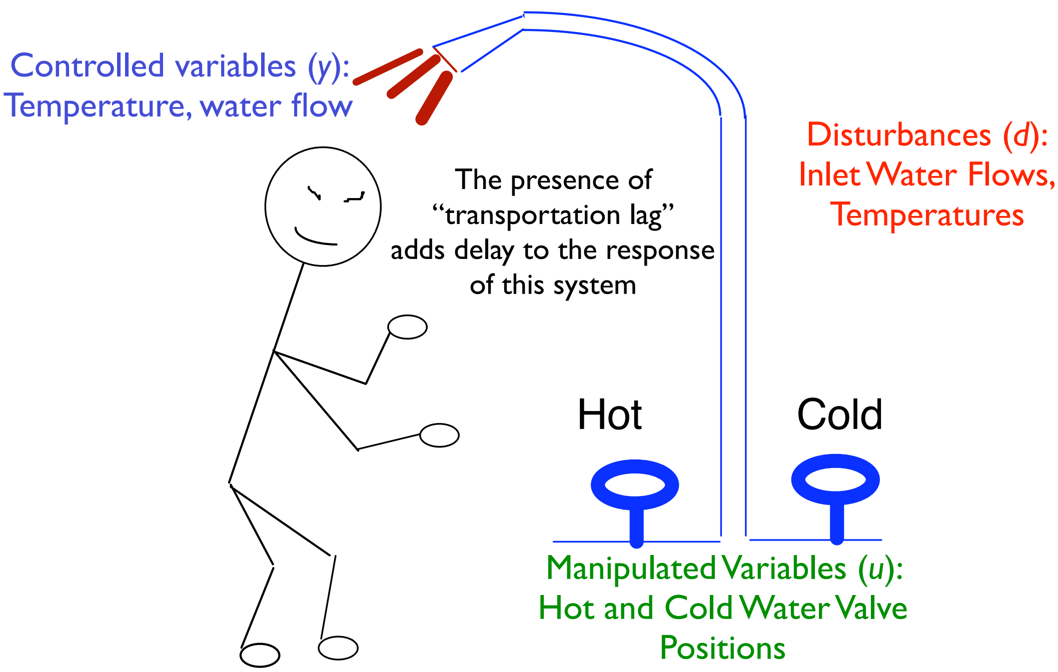
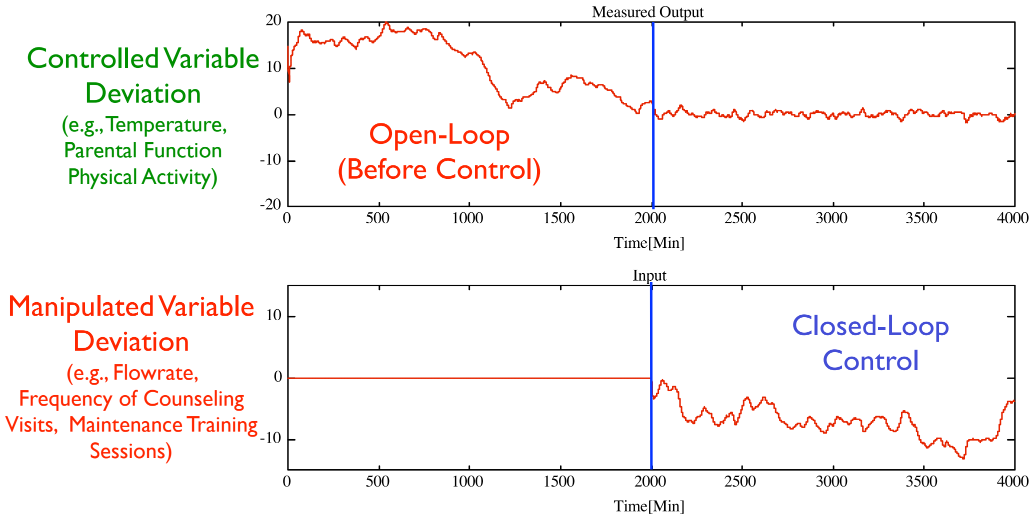


Objective: Adjust hot and cold water flows in response to changes in shower temperature and outlet flow caused by external factors.

From "Open-Loop" Operation to "Closed-Loop" Control

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



The transfer of variance (as depicted in this diagram) represents one of the major benefits of control systems engineering.

Control Engineering Concepts Are Not New to Psychology...

• Carver C.S. and M.F. Scheier. On the self-regulation of behavior. 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.

Enablers for Using Control Systems Engineering in Behavioral Interventions

- Increasing interest in optimizing behavioral interventions by personalizing these through *adaptive* interventions (Collins, Murphy, Bierman, 2004)
- Increasing availability of *intensive longitudinal data* (ILD; Walls and Schafer, 2006) through computing and mobile technologies that may be accomplishing *ecological momentary assessment* (EMA; Shiffman *et al*., 2008).
- Ability to "close the loop" through *ecological momentary interventions* (EMI) that take advantage of computing and mobile technology.
- Insights provided by behavioral theories and methods from quantitative psychology that influence both dynamic modeling and control strategy development.

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Suggested Reading No. 1

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Prevention Science, Vol. 5, No. 3, September 2004 (© 2004)

A Conceptual Framework for Adaptive Preventive Interventions

Linda M. Collins,[1,4] Susan A. Murphy,[2] and Karen L. Bierman[3]

Recently, *adaptive* interventions have emerged as a new perspective on prevention and treatment. Adaptive interventions resemble clinical practice in that different dosages of certain prevention or treatment components are assigned to different individuals, and/or within individuals across time, with dosage varying in response to the intervention needs of individuals. To determine intervention need and thus assign dosage, adaptive interventions use prespecified decision rules based on each participant's values on key characteristics, called tailoring variables. In this paper, we offer a conceptual framework for adaptive interventions, discuss principles underlying the design and evaluation of such interventions, and review some areas where additional research is needed.

KEY WORDS: adaptive interventions; prevention; research design.

For most of the history of research-based interventions aimed at prevention and treatment, the composition and dosage of these interventions have been *fixed*, in other words, a single composition and dosage has been offered to all program participants. For example, a school-based drug abuse prevention curriculum might be delivered to all sixth graders. Every component of the intervention that may be necessary for any particular participant is included in the curriculum, and each child is given the same intervention. Although it is recognized that individuals may have different intervention needs, it is expected that the intervention is in no way diluted or made counterproductive if components that are particularly relevant for an individual are combined with components that may have less, or even no, relevance for that individual.

Recently, *adaptive* interventions have emerged as a new perspective on research-based prevention and treatment. According to this perspective, the varying intervention needs of individuals may not be met optimally by using a single uniform composition and dosage. For this reason, an adaptive intervention assigns different dosages of certain program components across individuals, and/or within individuals across time. Dosage varies in response to the intervention needs of individuals, and dosages are assigned based on decision rules linking characteristics of the individual with specific levels and types of program components. In some adaptive interventions a dosage of zero is possible on a given component. This implies that there may be individuals who do not receive certain components at all, and that different types or versions of program components may be assigned to different individuals. Part of the conceptual appeal of the adaptive approach is its clear resemblance to clinical practice. However, in order to maintain replicability (see below), adaptive interventions entail the use of explicit decision rules, thus differing from most clinical practice.

Adaptive interventions are becoming more common, as prevention programs move in the direction

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[4]Correspondence should be directed to Linda M. Collins, 159 S. Henderson, University Park, Pennsylvania 16802; e-mail: lmcollins@psu.edu.

Adaptive Interventions

(Collins, Murphy, and Bierman, *Prevention Science*, 2004)

- In an *adaptive* intervention, treatment is *individualized* by the use of *decision rules* that determine how the treatment level and type should vary according to *tailoring variables (e.g.* measures of adherence and/or response) collected during past treatment.
- An effective adaptive intervention may result in the following advantages over fixed interventions:
  - Reduction of negative effects (e.g., stigma),
  - Reduction of inefficiency and waste,
  - Increased compliance,
  - Enhanced intervention potency
- In *time-varying* adaptive interventions, tailoring variables are measured periodically, so the intervention is adjusted on an on-going basis. *Note*: these are increasingly being referred to as *just-in-time* adaptive interventions.

Adaptive Preventive Intervention Illustration

(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.

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Drug and Alcohol Dependence 88S (2007) S31–S40
DRUG and ALCOHOL DEPENDENCE
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Using engineering control principles to inform the design of adaptive interventions: A conceptual introduction

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Abstract

The goal of this paper is to describe the role that control engineering principles can play in developing and improving the efficacy of adaptive, time-varying interventions. It is demonstrated that adaptive interventions constitute a form of feedback control system in the context of behavioral health. Consequently, drawing from ideas in control engineering has the potential to significantly inform the analysis, design, and implementation of adaptive interventions, leading to improved adherence, better management of limited resources, a reduction of negative effects, and overall more effective interventions. This article illustrates how to express an adaptive intervention in control engineering terms, and how to use this framework in a computer simulation to investigate the anticipated impact of intervention design choices on efficacy. The potential benefits of operationalizing decision rules based on control engineering principles are particularly significant for adaptive interventions that involve multiple components or address co-morbidities, situations that pose significant challenges to conventional clinical practice.

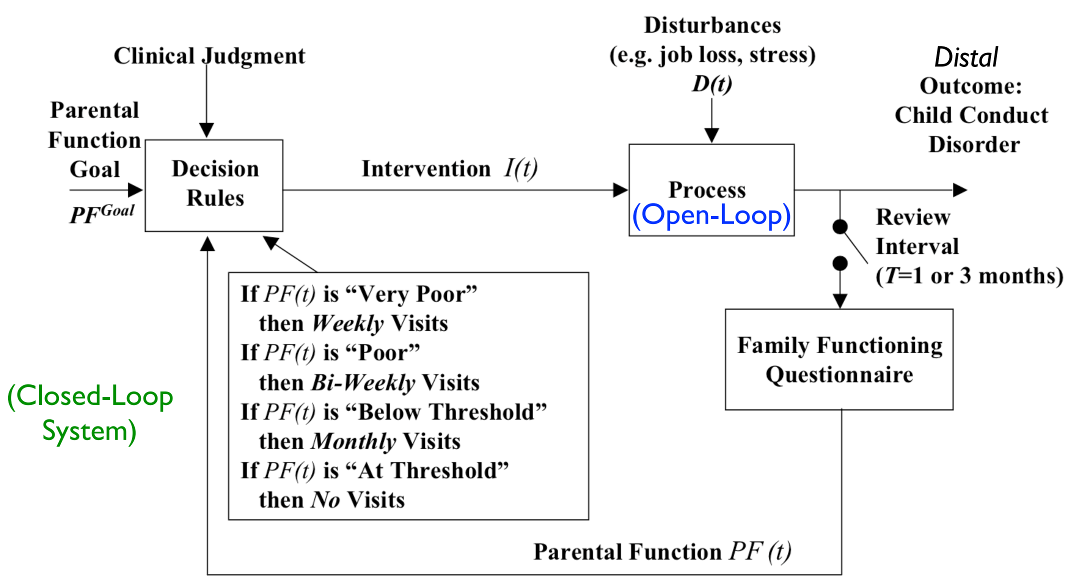
Keywords: Adaptive interventions; Engineering process control; Substance abuse prevention

1. Introduction

Adaptive interventions represent a promising approach to prevention and treatment. They are especially useful for prevention programs with numerous components aimed at different aspects of risk, and for treatment of chronic, relapsing disorders such as alcoholism, cigarette smoking, and other types of substance abuse. Contingency management, individualized treatments, stepped care programs, and case management all represent frameworks that enable the implementation of adaptive interventions. Adaptive interventions individualize therapy by the use of *decision rules*, which express how the therapy level and type should vary according to *tailoring variables* such as response to treatment, adherence, and treatment burden (Murphy et al., 2007; MC-DATS, 2004). Adaptive interventions differ from conventional fixed interventions in significant ways. In fixed interventions, the same dosage is applied to all program participants without taking into account any of their individual characteristics. In an adaptive intervention, different dosages of prevention or treatment components are assigned to different individuals and/or to the same individual across time, with dosage varying in response to the needs of the individual. For example, the composition of a computer-delivered drug abuse prevention program might be varied somewhat depending on the ethnicity of the recipient. Adaptive interventions are time varying when the adaptation is repeated throughout the intervention. For example, a smoking cessation program may periodically assess each participant's progress along the stages of the Transtheoretical Model (Velicer and Prochaska, 1999), and accordingly adjust how key components of the intervention are presented. Adaptive interventions are strikingly similar to sensible clinical practice, but in order to be successful, they must be much more tightly managed than typical clinical procedures. Interest in adaptive techniques is significant not only in the treatment of substance abuse (Sobell and Sobell, 1999; Velicer and Prochaska, 1999; Brooner and Kidorf, 2002; Murphy and McKay, Winter 2003/Spring 2004) but also in the treatment of hypertension (Glasgow et al., 1989), depression (Rush

Parental Function Feedback Loop *Block Diagram**

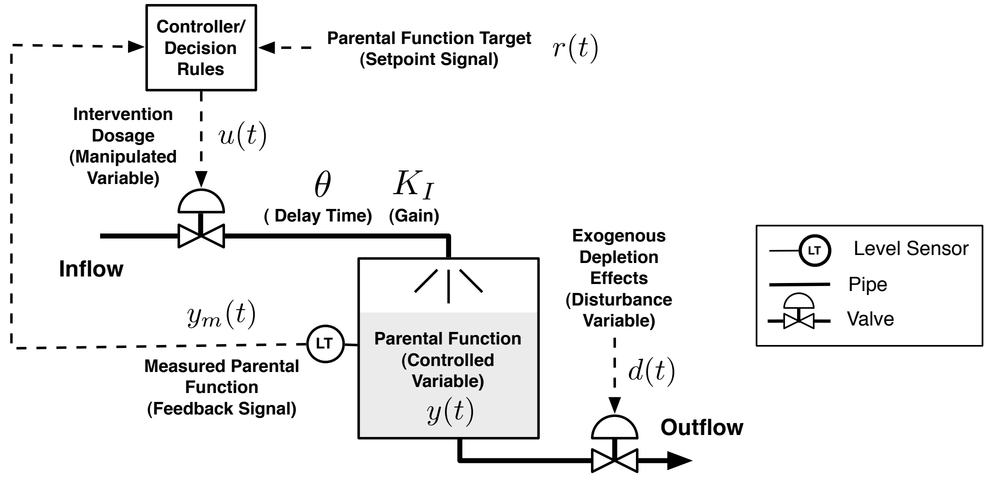
(to decide on home visits for families with at-risk children)



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 System

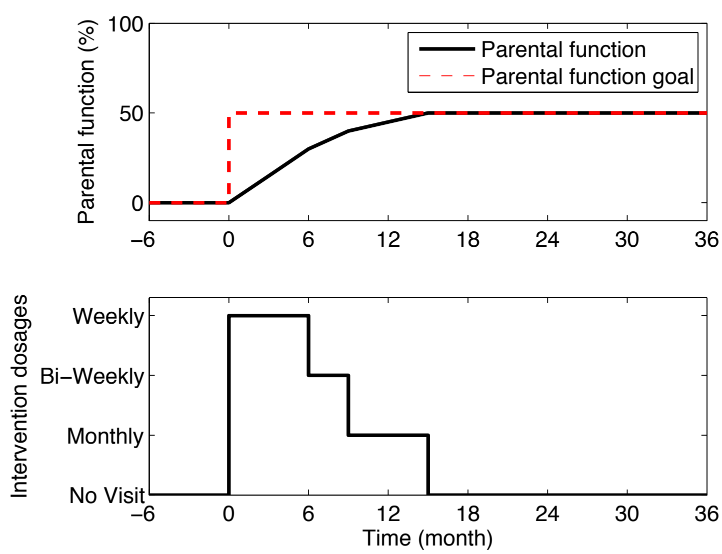
(Rivera, Pew, and Collins, "Using engineering control principles to inform the design of adaptive interventions," *Drug and Alcohol Dependence*, Vol. 88, Suppl. 2, May 2007, Pages S31-S40)



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

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)*).

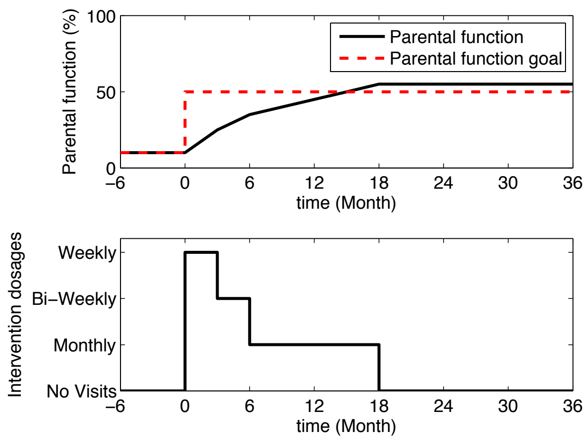
Parental Function - Counselor Home Visits Adaptive Intervention Single Participant Family Illustration



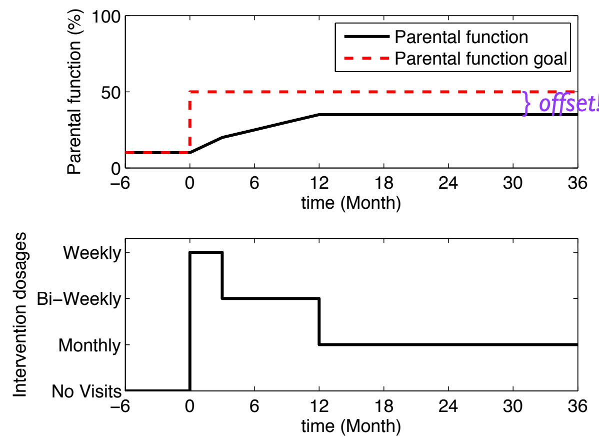
- The assigned dosage (frequency of counseling visits) decreases as the tailoring variable (parental function) increases, as prescribed by the decision rules.

Simple "IF-THEN" Rules May Not Be Optimal

No Depletion (*d(t)* = *0*)



High Depletion (*d(t)* = *5*)



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.

Engineering Control Design

- Based on a knowledge of the "open-loop" model, an optimized decision algorithm (i.e., the *controller*) can be designed to achieve improved "closed-loop" operation.

- Controller design is criterion-based; an *objective function* is chosen to minimize (or maximize) a metric related to achievement of outcomes.

- In general, controller sophistication will be a function of 1) model complexity and 2) desired performance requirements.

- This talk will focus on the use of Model Predictive Control (MPC) as described in Nandola and Rivera, *IEEE Transactions on Control Systems Technology* (10.1109/TCST.2011.2177525; published January 2013).

Suggested Reading No. 3

IEEE TRANSACTIONS ON CONTROL SYSTEMS TECHNOLOGY, VOL. 21, NO. 1, JANUARY 2013 121

An Improved Formulation of Hybrid Model Predictive Control With Application to Production-Inventory Systems

Naresh N. Nandola and Daniel E. Rivera, *Senior Member, IEEE*

***Abstract*—We consider an improved model predictive control (MPC) formulation for linear hybrid systems described by mixed logical dynamical (MLD) models. The algorithm relies on a multiple-degree-of-freedom parametrization that enables the user to adjust the speed of setpoint tracking, measured disturbance rejection and unmeasured disturbance rejection independently in the closed-loop system. Consequently, controller tuning is more flexible and intuitive than relying on objective function weights (such as move suppression) traditionally used in MPC schemes. The controller formulation is motivated by the needs of nontraditional control applications that are suitably described by hybrid production-inventory systems. Two applications are considered in this paper: adaptive, time-varying interventions in behavioral health, and inventory management in supply chains under conditions of limited capacity. In the adaptive intervention application, a hypothetical intervention inspired by the *Fast Track* program, a real-life preventive intervention for reducing conduct disorder in at-risk children, is examined. In the inventory management application, the ability of the algorithm to judiciously alter production capacity under conditions of varying demand is presented. These case studies demonstrate that MPC for hybrid systems can be tuned for desired performance under demanding conditions involving noise and uncertainty.**

***Index Terms*—Adaptive behavioral interventions, hybrid systems, model predictive control (MPC), production-inventory systems, supply chain management.**

I. Introduction

HYBRID systems are characterized by interactions between continuous and discrete dynamics. The term hybrid has also been applied to describe processes that involve continuous dynamics and discrete (logical) decisions [1], [2]. Applications of hybrid systems occur in many diverse settings; these include manufacturing, automotive systems, and process control. In recent years, significant emphasis has been given to modeling [1], [2], identification [3], [4], control [5], [6], estimation [7] and optimization [8], [9] of linear and nonlinear hybrid systems. A recent review paper [10] notes that despite the considerable interest within the control engineering community for model predictive control for hybrid systems, the field has not been fully developed, and many open challenges remain. Among these is the application to new areas outside of the industrial community, and the need for novel formulations that can be effectively used in noisy, uncertain environments. This paper represents an effort to obtain a flexible model predictive control (MPC) formulation displaying ease of tuning that is amenable to robust performance in hybrid systems, and its application in two nontraditional problem settings that can be expressed as production-inventory systems: adaptive interventions in behavioral health and inventory management in supply chains.

The production-inventory system is a classical problem in enterprise systems that has application in many problem arenas. Fig. 1 shows a diagram of a production-inventory system under combined feedback-feedforward control action. The production node is represented by a pipe, while the inventory component consists of fluid in a tank. The goal is to manipulate the inflow to the production node (i.e., starts) in order to replenish an inventory that satisfies exogeneous demand. The demand signal is broken down into forecasted and unforecasted components. A substantial literature exists that examines production-inventory systems from a control engineering standpoint [11]–[14]; recently, [15] examined both internal model control (IMC) and MPC for a linear production-inventory system with continuous inputs. The hybrid production-inventory system, in which production occurs at discrete levels (or is decided by discrete-event decisions) is an important yet less examined problem; we consider it the focus of this paper.

This paper highlights two distinct application areas that can be described as hybrid production-inventory systems. The first is adaptive interventions in behavioral health, which is a topic receiving increasing attention as a means to address the prevention and treatment of chronic, relapsing disorders, such as drug abuse [16]. In an adaptive intervention, dosages of intervention components (such as frequency of counseling visits or medication) are assigned to participants based on the values of tailoring variables that reflect some measure of outcome or adherence. Recent work has shown the relationship between forms of adaptive interventions and dynamical modeling and control of pro-

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D. E. Rivera is with the Control Systems Engineering Laboratory, School for Engineering of Matter, Transport, and Energy, Arizona State University, Tempe,

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.

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Model Predictive Control Conceptual Representation

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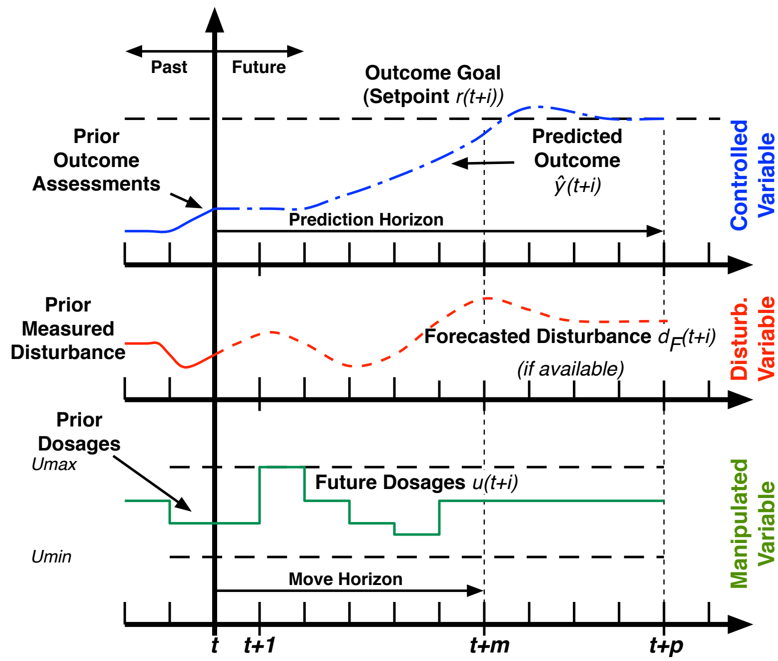

$$J = \overbrace{\sum_{\ell=1}^{p} Q_e(\ell)(\hat{y}(t+\ell|t) - r(t+\ell))^2}^{\text{Take Controlled Variables to Goal}} + \overbrace{\sum_{\ell=1}^{m} Q_{\Delta u}(\ell)(\Delta u(t+\ell-1|t))^2}^{\text{Penalize Changes in the Manipulated Variables}}$$

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Model Predictive Control Optimization Problem

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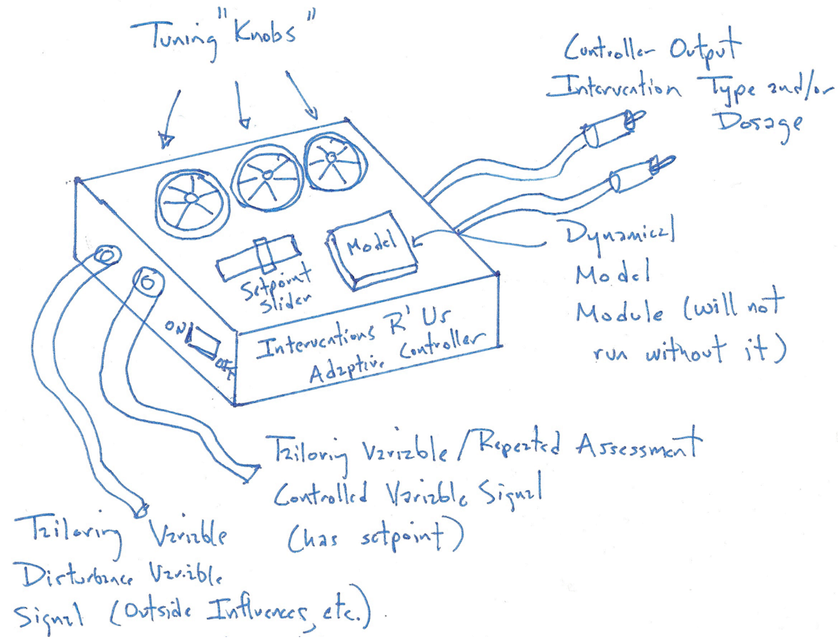
$$J = \overbrace{\sum_{\ell=1}^{p} Q_e(\ell)(\hat{y}(t+\ell|t) - r(t+\ell))^2}^{\text{Take Controlled Variables to Goal}} + \overbrace{\sum_{\ell=1}^{m} Q_{\Delta u}(\ell)(\Delta u(t+\ell-1|t))^2}^{\text{Penalize Changes in the Manipulated Variables}}$$

subject to restrictions (i.e., constraints) on:

- manipulated variable range limits (i.e., intervention dosage limits)
- the rate of change of manipulated variables (i.e., dosage changes)
- controlled and associated variable limits (i.e., limits on measured primary and secondary outcomes)

Many operating and clinical requirements can be expressed as constraint equations for the Model Predictive Control optimization problem.

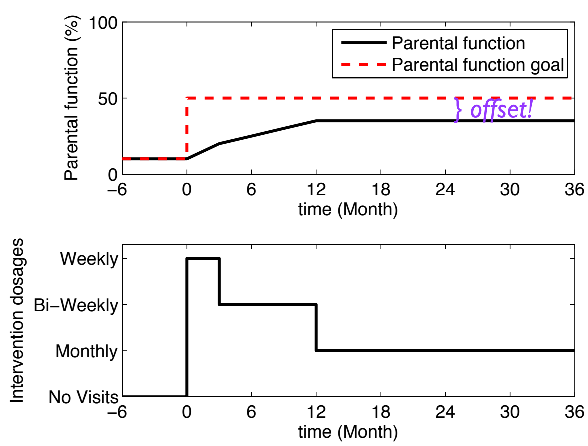
The Optimized Adaptive Intervention "Box"
(coming to a store near you...)



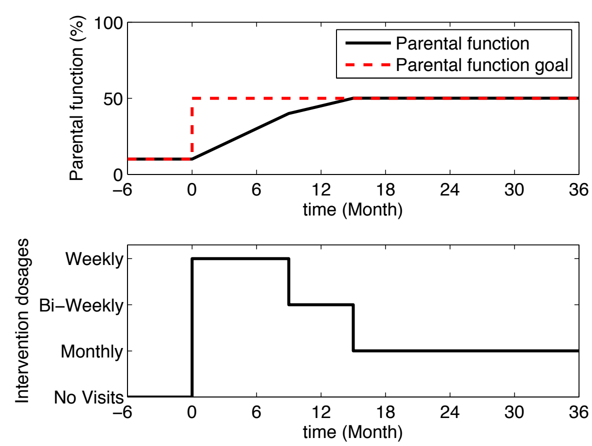
- A "hardware" view to what is often perceived a "hidden" technology.

Controller/Decision Rule Comparison
High Depletion Conditions ($d(t)$ = 5)

"IF-THEN" rules



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



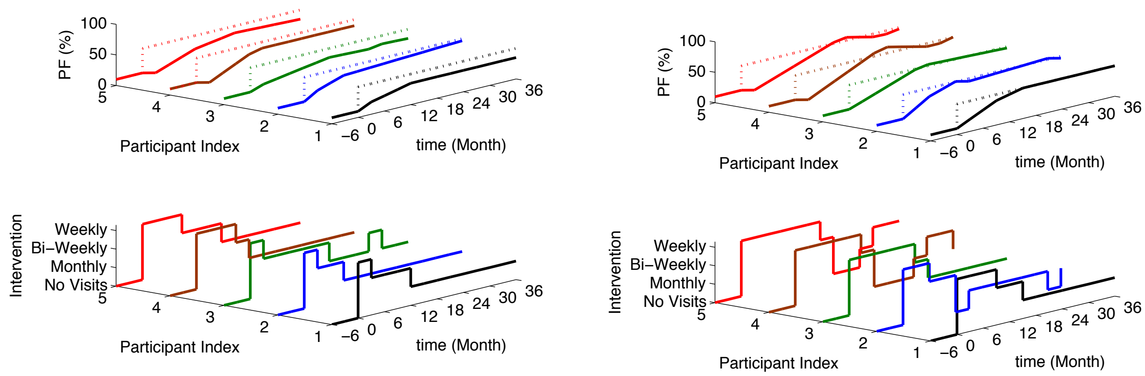
36 month intervention reviewed at quarterly intervals. *Offset* is eliminated in the MPC controller through judicious assignment of intervention dosages during the course of the intervention.

IF-THEN vs. MPC Comparison (Multiple Participants)

- 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") model.

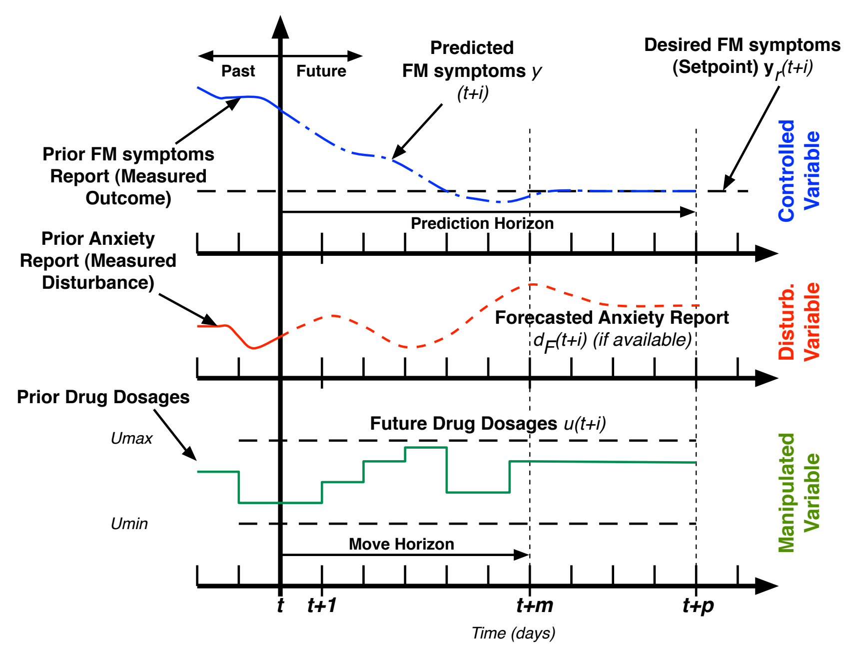
"IF-THEN" Decision Rules

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



- The MPC controller individually assigns 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.

Disturbances can also serve as tailoring variables (fibromyalgia intervention example)



$$\min_{\{[u(k+i)]_{i=0}^{m-1},\ [\delta(k+i)]_{i=0}^{p-1},\ [z(k+i)]_{i=0}^{p-1}\}} J \triangleq \sum_{i=1}^{p} \|(y(k+i) - y_r)\|^2_{Q_y}$$

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Model Predictive Control, Naltrexone Intervention for Fibromyalgia (FM)

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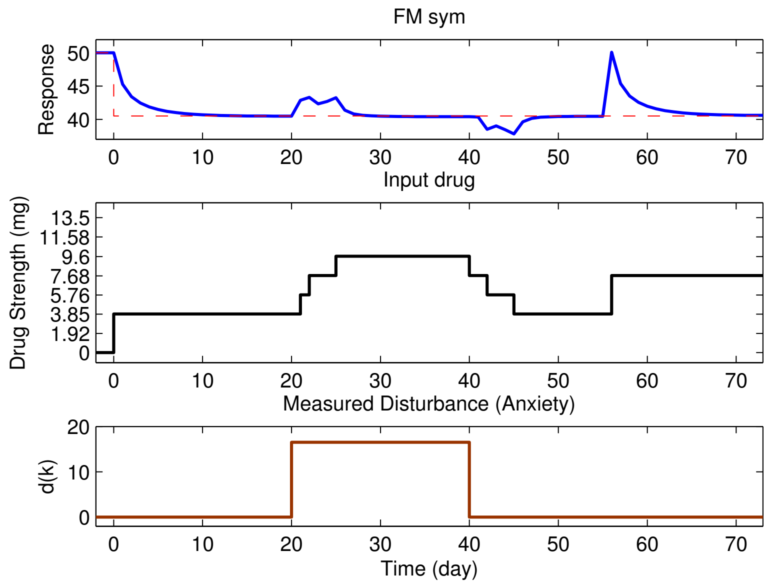

In combined feedback-feedforward control, both the FM symptom self-report (the controlled variable) and the anxiety self-report (a disturbance variable) serve as *tailoring variables.*

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Control Engineering Benefits

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- Ability to specify and track an operational goal for a personalized behavioral intervention, in lieu of a general determination of efficacy or effect sizes. *A significant paradigm change in behavioral science!*

- Controller tuning "knobs" enable customizing the intervention to a significant extent. This includes determining the "speed" of intervention and the responsiveness of the intervention to specific measurements.

- Many challenges remains:
  - how can one obtain dynamical systems models for behavioral interventions? (one approach: system identification).
  - can obtaining system identification models rely on behavioral theories to go beyond applying "black-box" techniques?

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Presentation Outline

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- What is meant by control systems engineering, and how can it improve behavioral interventions?
    - Hypothetical time-varying adaptive intervention (inspired by the *Fast Track* program) as a control system.
    - Application of Model Predictive Control (MPC).
- Some additional illustrations:
    - *Prevention of excessive gestational weight gain,*
    - Smoking cessation treatment using bupropion and counseling.
- Concluding remarks and acknowledgements.

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Gestational Weight Gain (GWG) Interventions

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- Over the past 20 years, the percentage of women gaining over 40 lbs (18 kg) during pregnancy has increased by 30%.
- Excessive Gestational Weight Gain (GWG) increases risk factors for pregnancy complications such as gestational diabetes, macrosomia, preeclampsia, and birth defects.
- Adaptive behavioral interventions that promote GWG within the 2009 Institute of Medicine (IOM) guidelines may hold particular promise for overweight and obese women.

Classification	Pre-gravid BMI (kg/m^2)	Target GWG (kg) Trimester	
		1	2-3
Underweight	<20	0.5 - 2.0	11.4 - 15.8
Normal	20 - 25	0.5 - 2.0	9.1 - 13.0
Overweight	25 - 30	0.5 - 2.0	6.0 - 8.6
Obese	> 30	0.5 - 2.0	4.4 - 7.0

Adaptive Intervention Overview

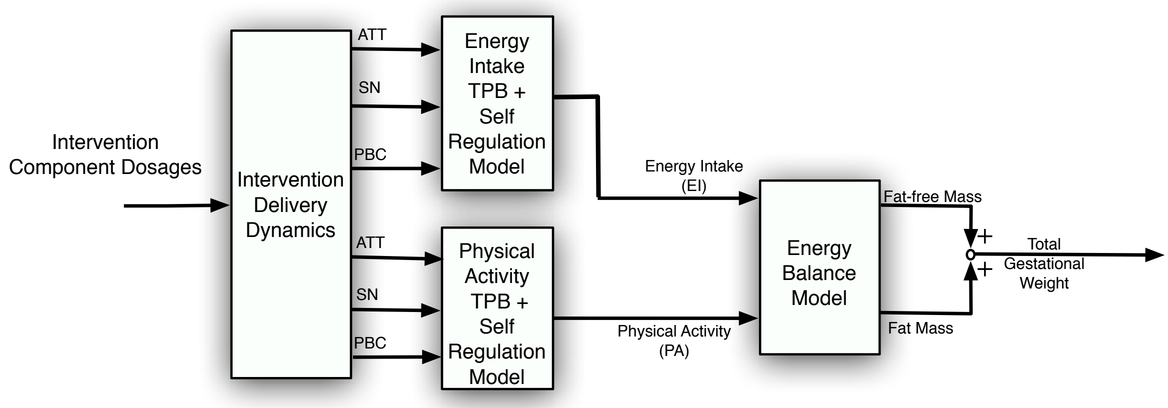
- Lead behavioral scientists: Danielle Downs (Kinesiology) and Jen Savage (Nutritional Sciences), Penn State University.

- Intervention components include dietary and physical activity (PA) education, individualized dietary and PA prescription, active learning, goal setting, self monitoring (using records and PA monitors).

- Theoretical influences include the Theory of Planned Behavior (TPB), and self-regulation.

- Measures assessed daily, weekly, bi-weekly, or pre- and post-assessment.

Schematic Representation for GWG Intervention Dynamics



An "open-loop" dynamical model for gestational weight gain consists of a system of integrated differential equations describing:

- Physiology (energy balance),
- Behavior change (Theory of Planned Behavior [TPB] and self-regulation).

Dong, Y., D.E. Rivera, D.M. Thomas, J.E. Navarro-Barrientos, D.S. Downs, J.S. Savage, and L.M. Collins, "A dynamical systems model for gestational weight gain behavioral interventions," *Proc. of the 2012 American Control Conference*, Montreal, pgs. 4059-4064.

Suggested Reading No. 4

Mathematical and Computer Modelling of Dynamical Systems
Vol. 17, No. 2, April 2011, 183–203

Taylor & Francis
Taylor & Francis Group

A dynamical model for describing behavioural interventions for weight loss and body composition change

J.-Emeterio Navarro-Barrientos[a†], Daniel E. Rivera[a*] and Linda M. Collins[b]

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(*Received 21 May 2010; final version received 19 August 2010*)

We present a dynamical model incorporating both physiological and psychological factors that predict changes in body mass and composition during the course of a behavioural intervention for weight loss. The model consists of a three-compartment energy balance integrated with a mechanistic psychological model inspired by the Theory of Planned Behaviour. This describes how important variables in a behavioural intervention can influence healthy eating habits and increased physical activity over time. The novelty of the approach lies in representing the behavioural intervention as a dynamical system and the integration of the psychological and energy balance models. Two simulation scenarios are presented that illustrate how the model can improve the understanding of how changes in intervention components and participant differences affect outcomes. Consequently, the model can be used to inform behavioural scientists in the design of optimized interventions for weight loss and body composition change.

Keywords: behavioural interventions; weight loss; obesity; body composition; energy balance; Theory of Planned Behaviour; dynamical systems

1. Introduction

Obesity rates in the United States have increased substantially in recent decades [1]. In 2000, the percentage of adults in the United States with body mass index (BMI) exceeding 30 was 19.8% [2]. The 2000 census reported that 27% of US adults do not engage in any physical activity, and only 24.4% of US adults consumed at least five servings of fruits and vegetables a day. Among the US adults participating in programs for losing or maintaining weight, only 17.5% were following the recommended guidelines for reducing calories and increasing physical activity [2]. More recently, the World Health Organization has revealed that 2.7 and 1.9 million deaths per year are attributable to low fruit and vegetable intake and low physical activity, respectively [3]. Unhealthy diet behaviours are responsible for 31% of the cases of ischemic heart disease, 11% of the cases of strokes and 19% of the cases of gastrointestinal cancer.

Because obesity represents a preventable cause of premature morbidity and mortality, much research activity has been devoted to understanding its causes, and a number of diverse solutions have been proposed. Some of these have major disadvantages; for instance

Fluid Analogy for the Theory of Planned Behavior

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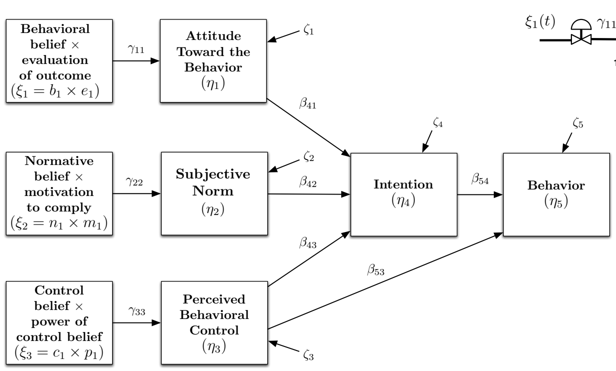
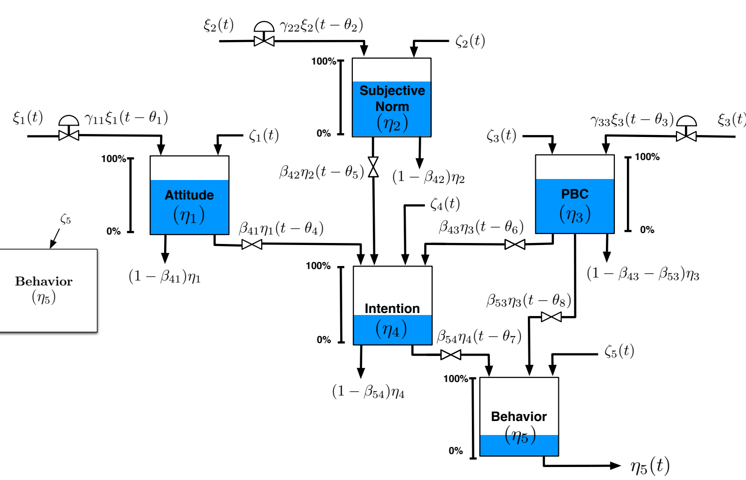
Navarro-Barrientos, J.E., D.E. Rivera, and L.M. Collins, "A dynamical model for describing behavioural interventions for weight loss and body composition change," *Mathematical and Computer Modelling of Dynamical Systems*, Volume 17, No. 2, Pages 183-203, 2011.





Any path diagram can be expressed into a corresponding fluid analogy described by a system of differential equations!

Theory of Planned Behavior Dynamical First-Order Model

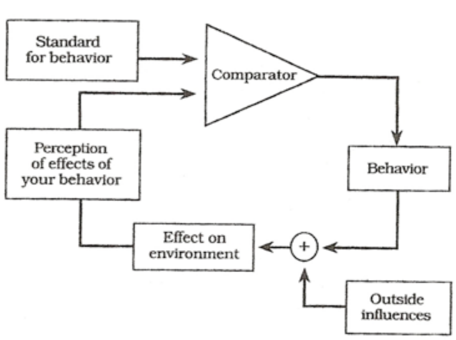
The conservation principle (Accumulation = Inflow − Outflow) leads to the following system of differential equations:

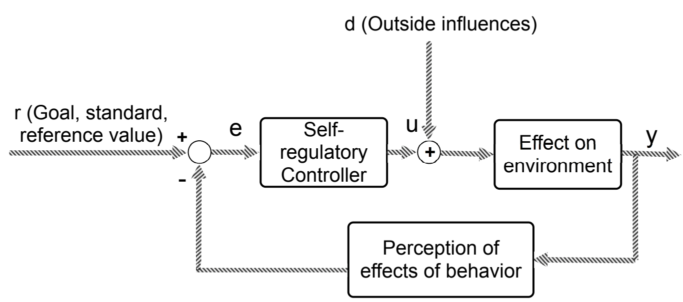
$$
\begin{aligned}
\tau_1 \frac{d\eta_1}{dt} &= \gamma_{11}\xi_1(t-\theta_1) - \eta_1(t) + \zeta_1(t) \\
\tau_2 \frac{d\eta_2}{dt} &= \gamma_{22}\xi_2(t-\theta_2) - \eta_2(t) + \zeta_2(t) \\
\tau_3 \frac{d\eta_3}{dt} &= \gamma_{33}\xi_3(t-\theta_3) - \eta_3(t) + \zeta_3(t) \\
\tau_4 \frac{d\eta_4}{dt}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

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.

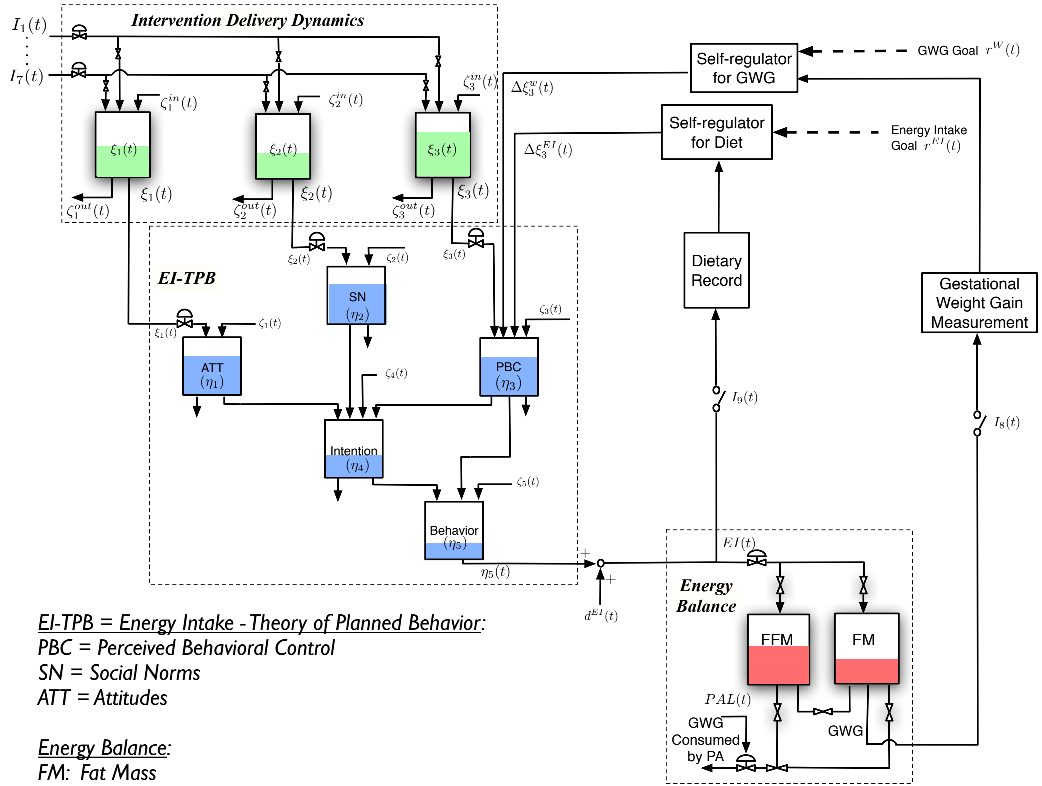
Self-Regulation of Behavior (Carver and Scheier, 1998)

- Self-regulation reflects the capacity of individuals to alter their own behavior, enabling them to adjust their actions to a broad range of social and situational demands.
- Self-regulation can be represented as a feedback control system that is enhanced by repeated assessment of important outcomes in an intervention.





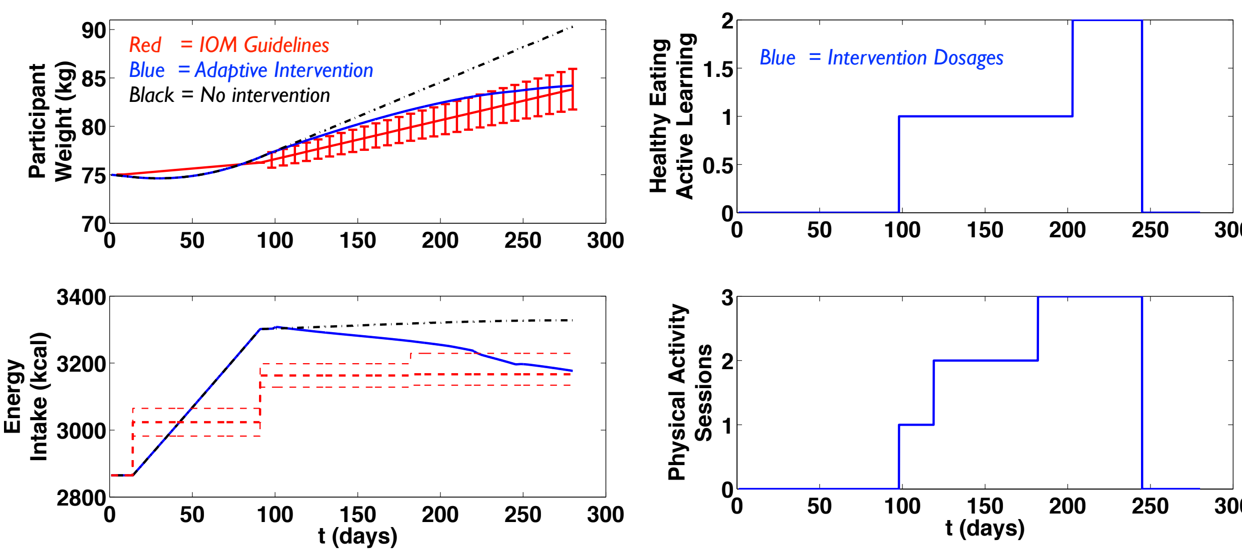
Gestational Weight Gain Intervention Fluid Analogy (Energy Intake Only)



EI-TPB = Energy Intake - Theory of Planned Behavior:
PBC = Perceived Behavioral Control
SN = Social Norms
ATT = Attitudes

Energy Balance:
FM: Fat Mass
FFM: Fat-Free Mass

Representative GWG Intervention Simulation Results



Dosage changes over time can be determined optimally using this dynamical systems model as the internal model "module" in Model Predictive Control.

GWG Adaptive Intervention: Challenges and Opportunities

- The use of the Theory of Planned Behavior and self-regulation guide the structure of the dynamical model, and form the basis for an interesting *semi-physical* system identification problem.
- How does one design an experimental trial to properly estimate this model?

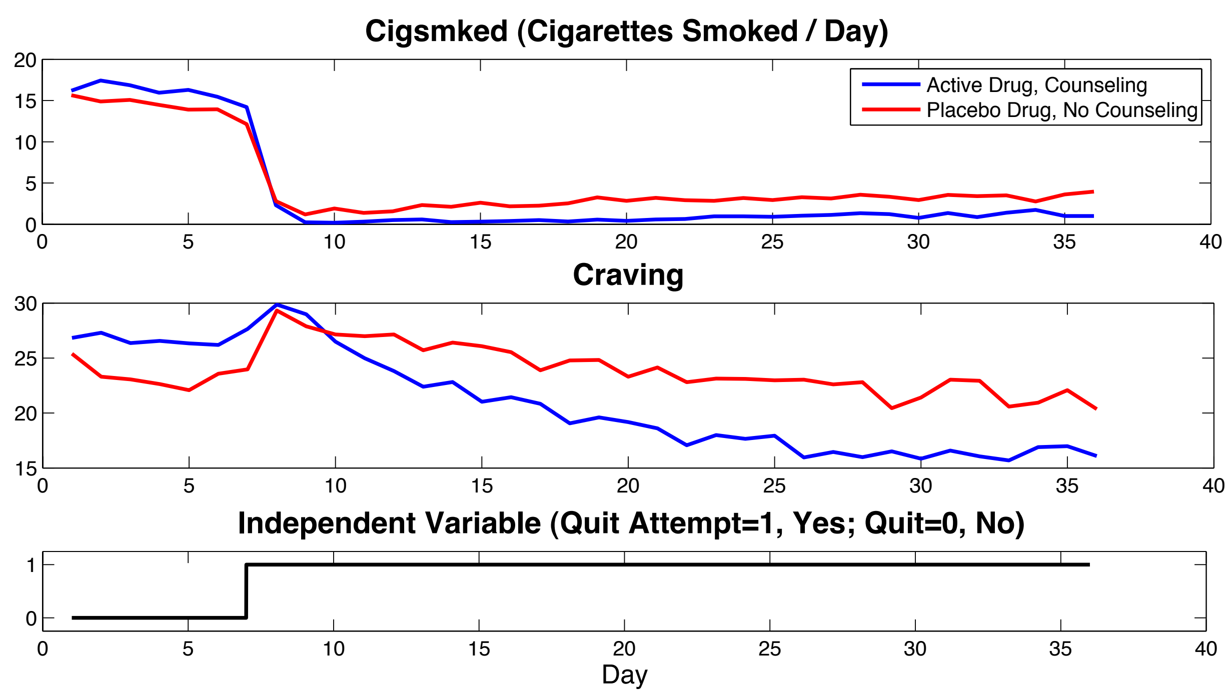
Presentation Outline

- What is meant by control systems engineering, and how can it improve behavioral interventions?
  - Hypothetical time-varying adaptive intervention (inspired by the *Fast Track* program) as a control system.
  - Application of Model Predictive Control (MPC).
- Some additional illustrations:
  - Prevention of excessive gestational weight gain,
  - *Smoking cessation treatment using bupropion and counseling.*
- Concluding remarks and acknowledgements.

Smoking Cessation Intervention (courtesy UW-CTRI)

- Data from study described in McCarthy *et al.*, *Addiction*, Vol. 103, pgs. 1521-1533, 2008. Active drug is bupropion SR.
- 11 week study; randomization (*n = 463*)
  - Drug: Drug, Placebo
  - Counseling: Yes, No
- Treatment Conditions:
  - Active Drug with Counseling (AC; *n=101*)
  - Active Drug, No Counseling (ANc; *n = 101*)
  - Placebo with Counseling (PC; *n =100*)
  - Placebo, No Counseling (PNc ; *n =101*)
- *T = 42* daily observations for each participant

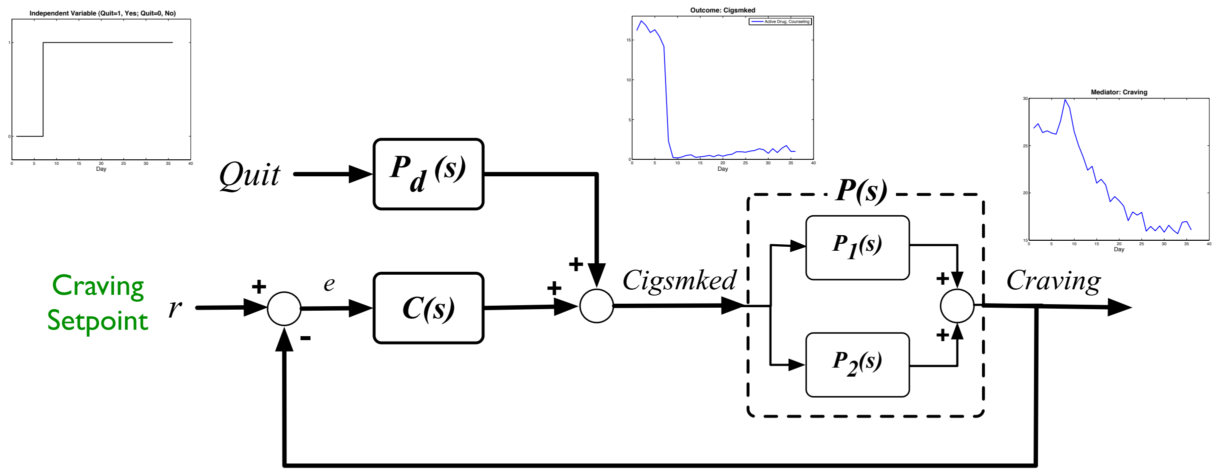
Group Average Data



- Comparison of craving scores versus quit for two treatment groups (active drug with counseling (AC, blue) vs. placebo-no counseling (PNc, red)).

Self-Regulation Model for Smoking Behavior
(Timms et al., SYSID 2012; *Int. J. Control* submitted)

- Craving-Cigsmked relationship described by *self-regulation* (Carver & Scheier, 1998); also *urge regulation* (Walls and Rivera, 2009 Society for Prev. Research)



P(s) ≡ Craving generation process

C(s) ≡ Craving self-regulator

$P_d(s)$ ≡ Effect of quit attempt

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Smoking Cessation System Identification Modeling Results

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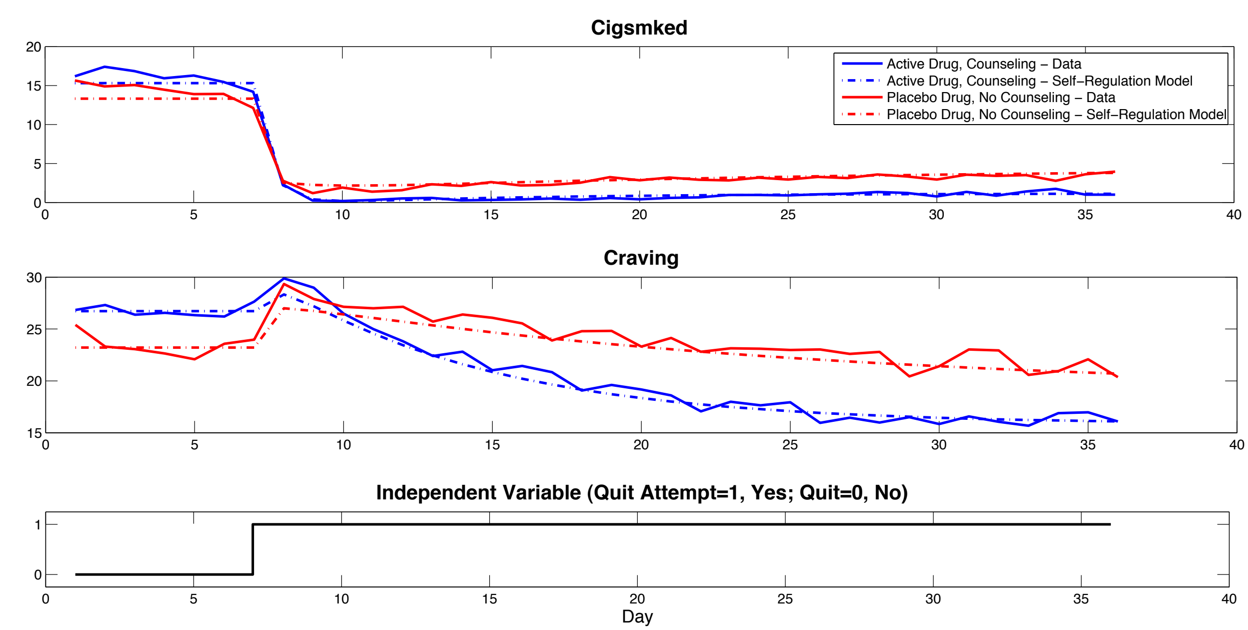
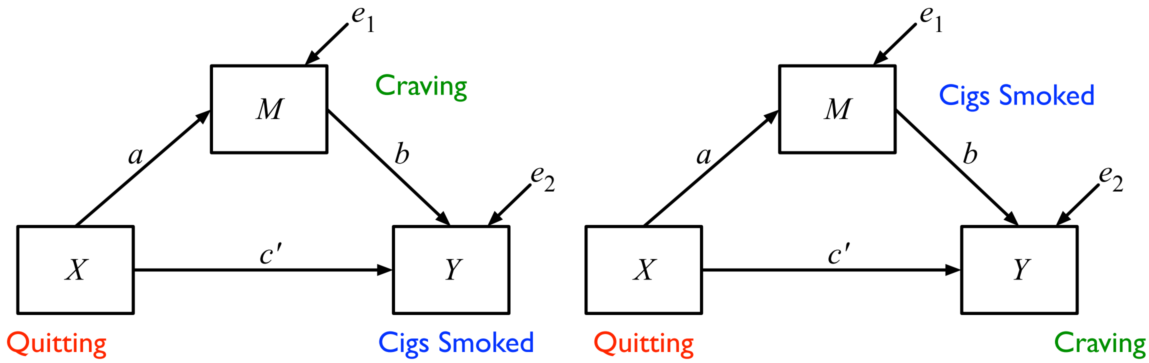
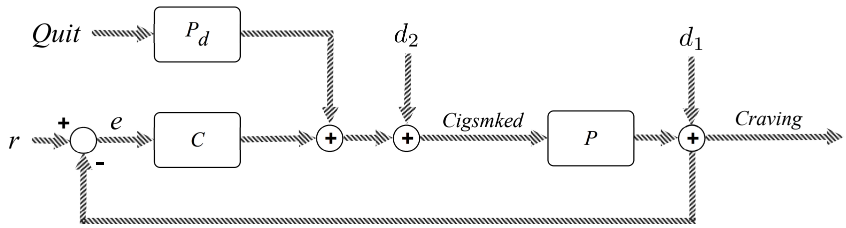


- High goodness-of-fit from parsimonious dynamical system models.
- Urge self-regulator eqn (*C*) can be reverse-engineered from data.

Mediation (top) or Self-Regulation (bottom)?

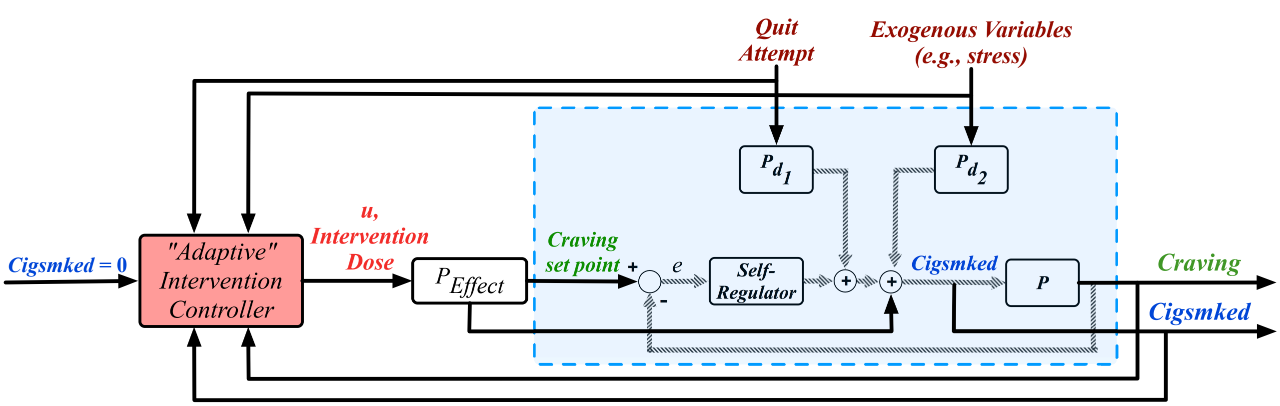




Our analysis suggests that a feedback model involving the self-regulation of craving through smoking describes the smoking process more comprehensively and parsimoniously than mediation analysis.

Smoking Cessation Interventions

- *Long-term goal:* optimizing smoking interventions using control systems engineering
  - Systematic, personalized assignment of intervention dosages
  - Controller can also be made *adaptive* with respect to characteristics such as gene-environment interactions, etc.



Presentation Outline

- What is meant by control systems engineering, and how can it improve behavioral interventions?
  - Hypothetical time-varying adaptive intervention (inspired by the *Fast Track* program) as a control system.
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- Some additional illustrations:
  - Prevention of excessive gestational weight gain,
  - Smoking cessation treatment using bupropion and counseling.
- *Concluding remarks and acknowledgements.*

Topics of Interest

- How can we develop informative, practical, and ethical experimental protocols for better understanding the dynamics of behavior change and optimizing behavioral interventions?
- Representing additional behavioral theories (e.g., Social Cognitive Theory) in terms of dynamical systems and control engineering.
- Enhancing (or invalidating) behavioral theories relying on intensive longitudinal data (ILD) and ecological momentary assessment (EMA).
- Closing the loop: optimized adaptive interventions and ecological momentary interventions (EMI).

mHealth/mobile interventions

TBM

Health behavior models in the age of mobile interventions: are our theories up to the task?

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[3]National Institute of Health, National Cancer Institute, 6130 Executive Boulevard, EPN 4082, Bethesda, MD 20892-7335, USA
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doi: 10.1007/s13142-011-0021-7

Abstract
Mobile technologies are being used to deliver health behavior interventions. The study aims to determine how health behavior theories are applied to mobile interventions. This is a review of the theoretical basis and interactivity of mobile health behavior interventions. Many of the mobile health behavior interventions reviewed were predominately one way (i.e., mostly data input or informational output), but some have leveraged mobile technologies to provide just-in-time, interactive, and adaptive interventions. Most smoking and weight loss studies reported a theoretical basis for the mobile intervention, but most of the adherence and disease management studies did not. Mobile health behavior intervention development could benefit from greater application of health behavior theories. Current theories, however, appear inadequate to inform mobile intervention development as these interventions become more interactive and adaptive. Dynamic feedback system theories of health behavior can be developed utilizing longitudinal data from mobile devices and control systems engineering models.

Keywords
Mobile phones, Handheld computers, Health behavior interventions, Smoking cessation, Weight management,

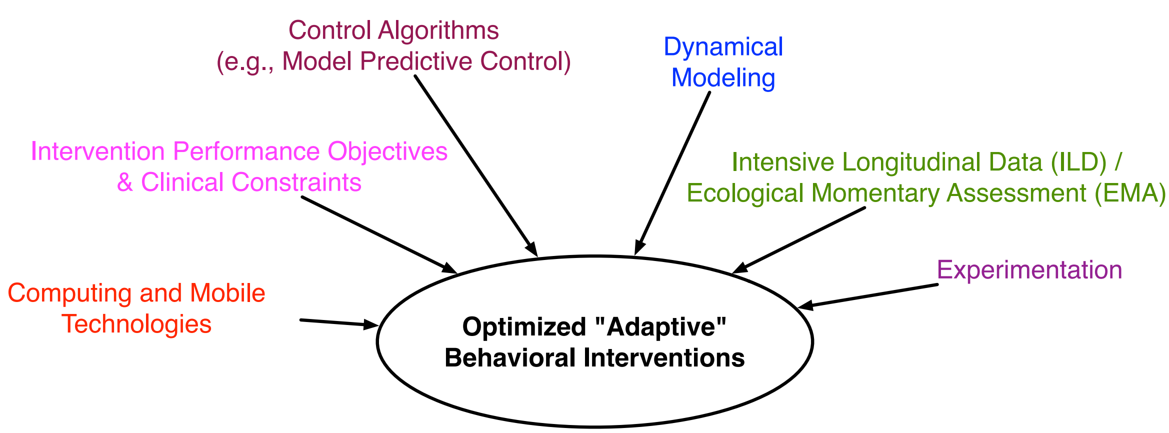
Implications

Practice: Mobile technologies are rapidly evolving as a method for delivering health behavior interventions that can be tailored to the individual throughout the intervention, but the content and timing of these interventions have not been consistently grounded in health behavior theories, so practitioners need to consider the theoretical and empirical basis of mobile health behavior interventions.

Policy: Investment in the development of mobile health behavior interventions needs to be balanced with investment in theoretically grounded content development and evaluation procedures that are responsive to this rapidly evolving area.

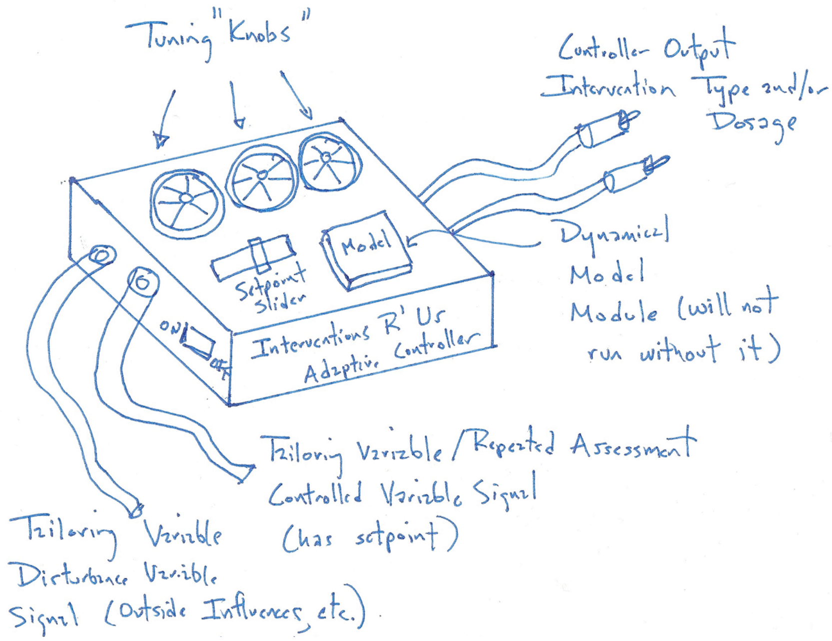
Research: In addition to the responsive evaluation of mobile health behavior interventions, researchers need to utilize these applications to test and advance more dynamic health behavior theories, taking advantage of control systems engineering and other dynamic feedback models to advance new theories that can be better applied to the intensive adaptability possible from mobile health behavior interventions.

The End Goal: Optimized Behavioral Interventions



A myriad of technologies must come together in order to apply *system identification and control systems engineering principles* to obtain optimal "adaptive" behavioral interventions.

The Optimized Adaptive Intervention "Box" (*coming to a store near you...*)



- A "hardware" view to what is often perceived a "hidden" technology.

Presentation Summary

- *Adaptive behavioral interventions* constitute dynamical systems that are amenable to system identification and control engineering approaches.
- *Intensive longitudinal data* (ILD) and *ecological momentary assessment* (EMA) can lead to dynamical models that better characterize both the effectiveness of treatment and the role of external variables.
- Behavioral theories such as the *Theory of Planned Behavior* and *self-regulation* can be useful in determining model structure and signal relationships.
- The dynamical system models that are obtained from this analysis enable intervention optimization using *control systems engineering*. This represents a major paradigm shift in behavioral health.
- A major challenge lies in developing novel experimental protocols that are informative yet acceptable within clinical settings.

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Looking to the Future

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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.

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Final Remarks

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- Terminology, background, and different "world views" can present challenges; nonetheless, the future is ripe with opportunities in this field.

Final Suggested Reading

http://csel.asu.edu/downloads/Publications/AdaptivePrevention/Rivera_SYSID_2012_plenary_preprint.pdf

Preprint of paper to be presented at the 16th IFAC Symposium on System Identification (SYSID 2012), Brussels, Belgium, July 11-13, 2012.

Optimized behavioral interventions: what does system identification and control engineering have to offer?

Daniel E. Rivera *

* *Control Systems Engineering Laboratory, School for Engineering of Matter, Transport, and Energy, Arizona State University, Tempe AZ 85287-6106 USA. Email: daniel.rivera@asu.edu*

Abstract: The last decade has witnessed an increasing interest in applying systems science concepts for problems in behavioral health, and using these to inform the design, analysis, and implementation of optimized interventions. How can system identification and control engineering impact interventions for chronic, relapsing disorders such as drug abuse, cigarette smoking and obesity? The paper addresses this question by focusing on the problem of time-varying "adaptive" interventions. In an adaptive intervention, dosages of intervention components are assigned based on the assessed values of *tailoring variables* that reflect some outcome measure (e.g., number of cigarettes smoked, parental function) or adherence (e.g, days abstinent). Because time-varying adaptive interventions constitute closed-loop dynamical systems, they are correspondlngly amenable to control engineering solutions. System identification is enabled by intensive longitudinal data (ILD) that can be obtained in the field via ecological momentary assessment (EMA); this creates the availability of rapidly sampled, continuous-time assessments from which dynamical system behavior can be discerned and modeled. How can system identification and control be applied in this broad setting is demonstrated with a number of illustrative problems: dynamic modeling and hybrid model predictive control of low-dose naltrexone as treatment for fibromyalgia, a chronic pain condition; modeling of a smoking cessation intervention involving bupropion and counseling; constructing a dynamic model of an intervention for preventing excessive weight gain during pregnancy, and Model-on-Demand Model Predictive Control in a hypothetical intervention based on the *Fast Track* program for assigning the frequency of home counseling visits to families with at-risk children.

Keywords: social and behavioral sciences, system identification, control engineering, adaptive behavioral interventions, hybrid model predictive control, experiment design

Reading and Reference List
(available from the CSEL website)

Reading and Reference List
Optimized Behavioral Interventions: What Does Control Systems Engineering Have to Offer?

Daniel E. Rivera, Ph.D.
School for Engineering of Matter, Transport, and Energy,
Arizona State University, Tempe, AZ 85287-6106,
e-mail: daniel.rivera@asu.edu; http://csel.asu.edu/health

An excellent introduction to the topic of adaptive interventions:

[1] Collins, L.M., S.A. Murphy, and K.L. Bierman, "A conceptual framework for adaptive preventive interventions," *Prevention Science*, **5**, No. 3, pgs. 185-196, 2004.

Our initial paper, inspired by [1], on the relationship between adaptive interventions and control engineering:

[2] 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*, **88**, Suppl. 2, May 2007, pgs. S31 - S40.

A report that describes the technical content in [2] in more detail:

[3] 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, available from http://csel.asu.edu/adaptiveintervention (select item 4).

A plenary talk I gave in July 2012 at the 16th IFAC Symposium on System Identification (SYSID 2012). This paper summarizes much of our efforts to date:

[4] Rivera, D.E., "Optimized behavioral interventions: what does system identification and control engineering have to offer? *16th IFAC Symposium on System Identification (SYSID 2012)*, Brussels, Belgium, July 11-13, 2012. Preprint available from http://csel.asu.edu/adaptiveintervention (select item 30).

Work from our laboratory showing how Model Predictive Control can be used for decision-making in adaptive behavioral interventions:

[5] 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. Preprint available from http://csel.asu.edu/adaptiveintervention (select item 13).

[6] Nandola, N. and D.E. Rivera, "An improved formulation of hybrid Model Predictive Control with application to production-inventory systems, *IEEE Transactions on Control Systems Technology*, http://dx.doi.org/10.1109/TCST.2011.2177525, early access.

Paper appearing in the inaugural issue of TBM focused on mobile health interventions, to which we contributed some dynamical systems and control engineering perspectives:

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Acknowledgments

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- Danielle Downs (Kinesiology) and Jen Savage (Nutritional Sciences), Penn State University.
- Diana Thomas, Mathematics, Montclair State University.
- Megan Piper and Tim Baker, Univ. of Wisconsin - Dept. of Medicine and Center for Tobacco Research and Intervention.
- Ted Walls, Psychology, Univ. of Rhode Island.
- Patty Mabry, Liz Ginexi, and Bill Riley, National Institutes of Health (US)
- *Eric Hekler, Matt Buman, and Marc Adams, ASU School of Nutrition and Health Promotion.*
- Constantino Lagoa, Electrical Engineering, Penn State University
- Naresh Nandola, Ph.D. (currently with ABB-Bangalore) and J. Emeterio Navarro-Barrientos, Ph.D. (currently with GFaI, Berlin)

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Control Systems Engineering Lab Team

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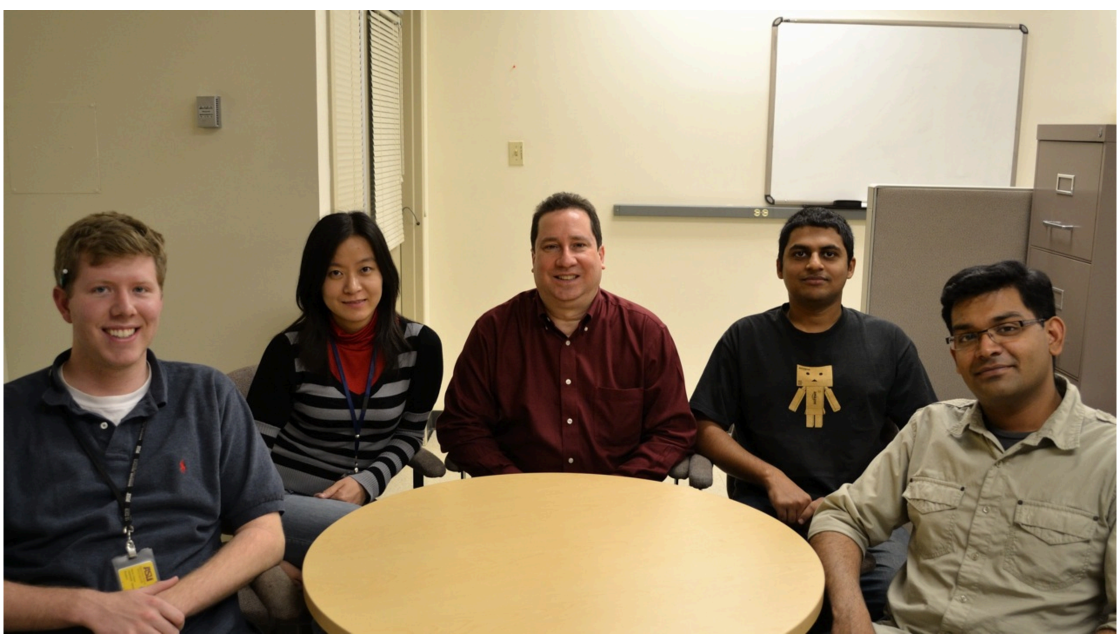

Kevin Timms Shirley Dong Daniel Rivera Sunil Deshpande Nikhil Poothakandiyil

César Martin (*not present*)

Sponsored Projects

- 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.

- K25DA021173, "Control engineering approaches to adaptive interventions for fighting drug abuse," *Mentored Quantitative Research Scientist Award,* Mentors: L.M. Collins (Penn State) and S.A. Murphy (Michigan).

Projects funded by the US National Institutes of Health: NIDA (National Institute on Drug Abuse) and OBSSR (Office of Behavioral and Social Sciences Research).

http://csel.asu.edu/health

Thank you for your attention!

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