

Control Of SAG Mills And Its Challenges

Bill Tubbs

PhD Student, School of Mining, UBC

Supervisors: Sanja Miskovic, Bhushan Gopulani

August 29, 2019

My Background

Technical Support Engineer



Operations Management
Consultant



Manager, Environmental
Permitting & Regulation



Manager, Climate & Energy



Energy Optimization Lead



Independent Consultant



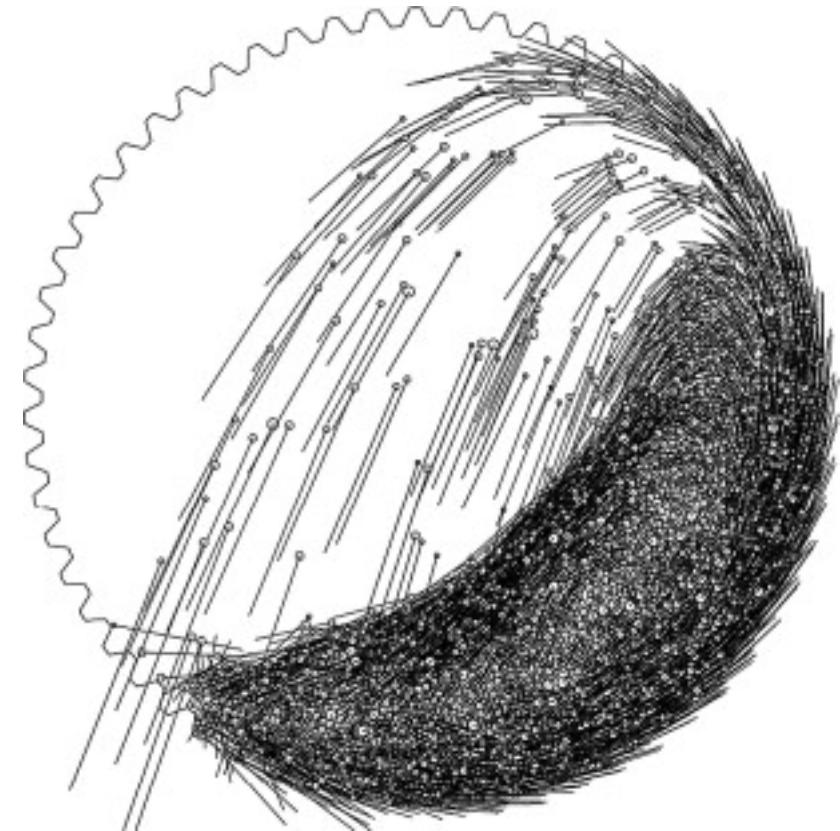
Background



SAG Mills Are Used In Large Mining Operations To Grind Crushed Ore Prior To Processing To Recover Valuable Metals

Background

- Grinding occurs inside a rotating drum-shaped mill containing rocks, water, and steel balls
- Size of rock particles is reduced by two processes:
 - *Impact breakage* due to cataracting motion
 - *Attrition* due to cascading motion

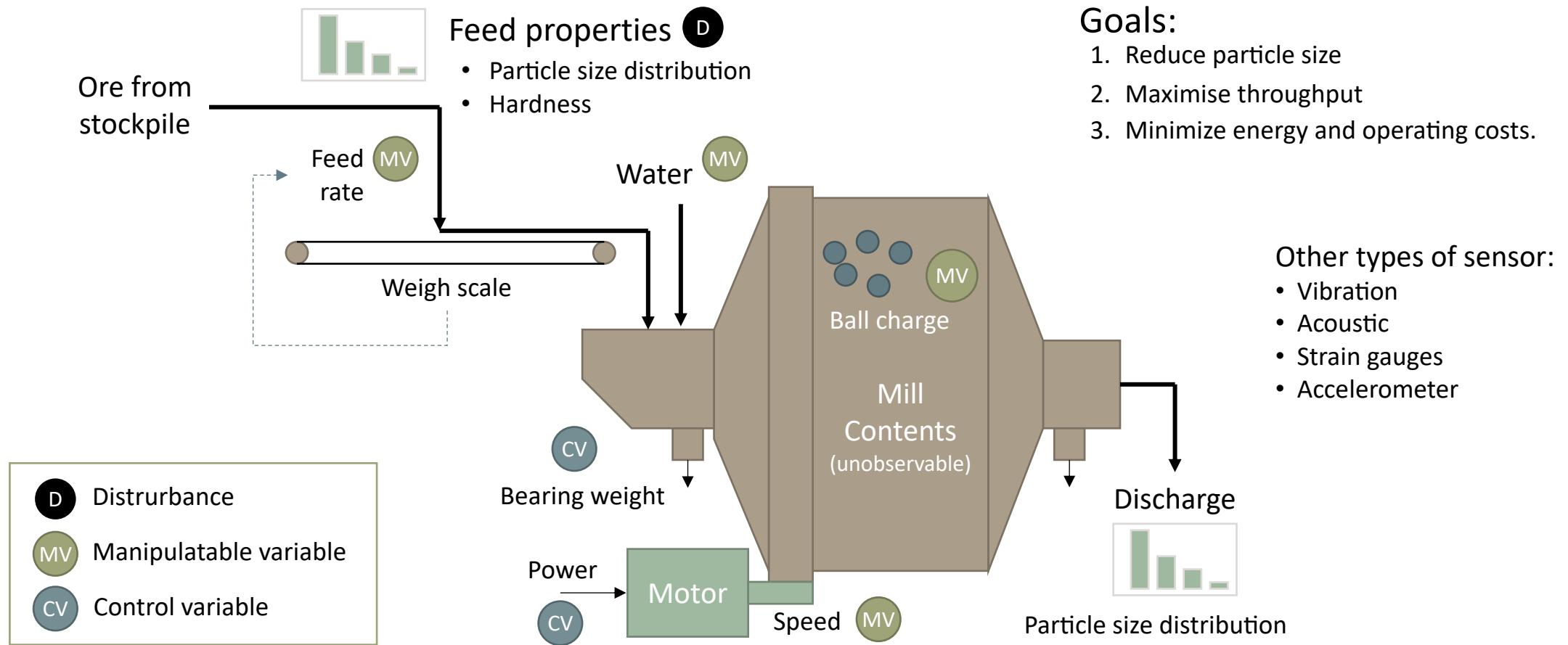


Video simulation: <https://vimeo.com/266660541>

Source: <https://www.sciencedirect.com/science/article/pii/S0892687513002926>

SAG Mills Are Used In Large Mining Operations To Grind Crushed Ore Prior To Processing To Recover Valuable Metals

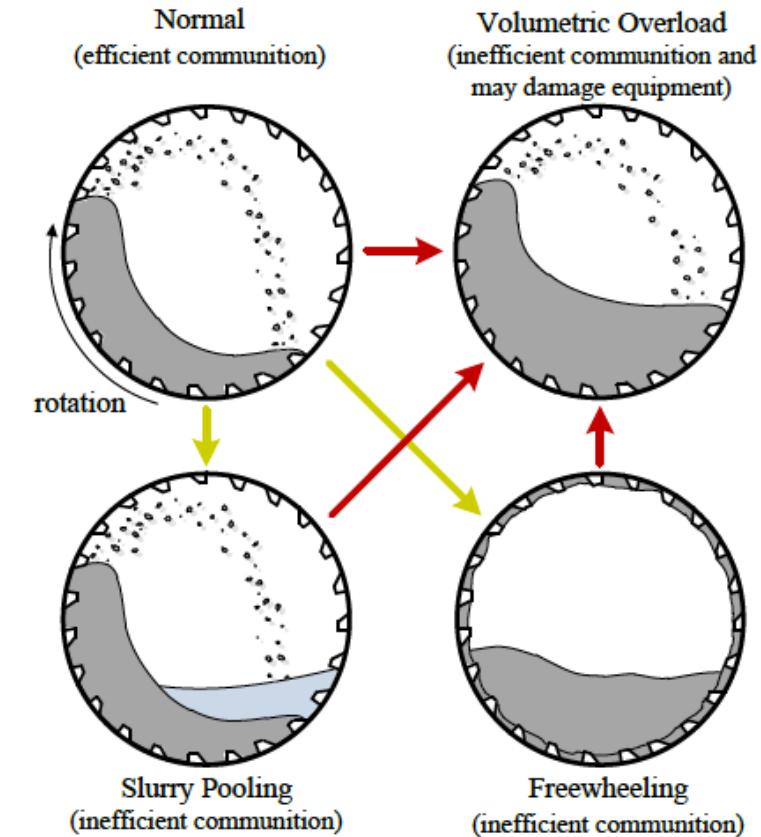
Background



Multi-Input, Multi-Output (MIMO) System With Unobservable Internal State

Process Characteristics

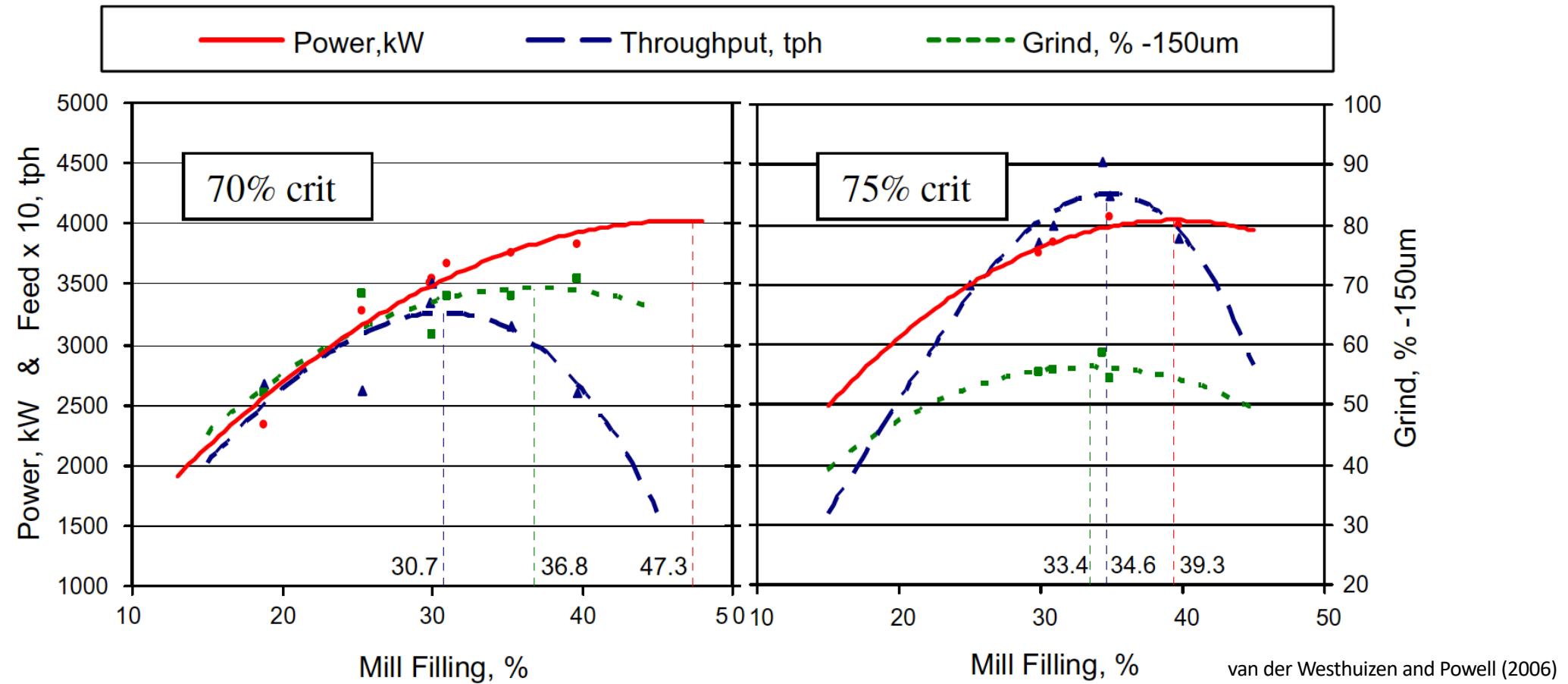
- Control challenges
 - Strong, unobservable disturbances
 - Partially-observable state
 - Non-linear dynamics
 - Circulating load
 - Slow response
 - Noise, measurement error
 - Unstable states
 - Stochastic (rock breakage)
 - Non-stationary (liner and ball wear)
- Probably impossible to build precise model from first principles



Source: McLure and Gopaluni (2015)

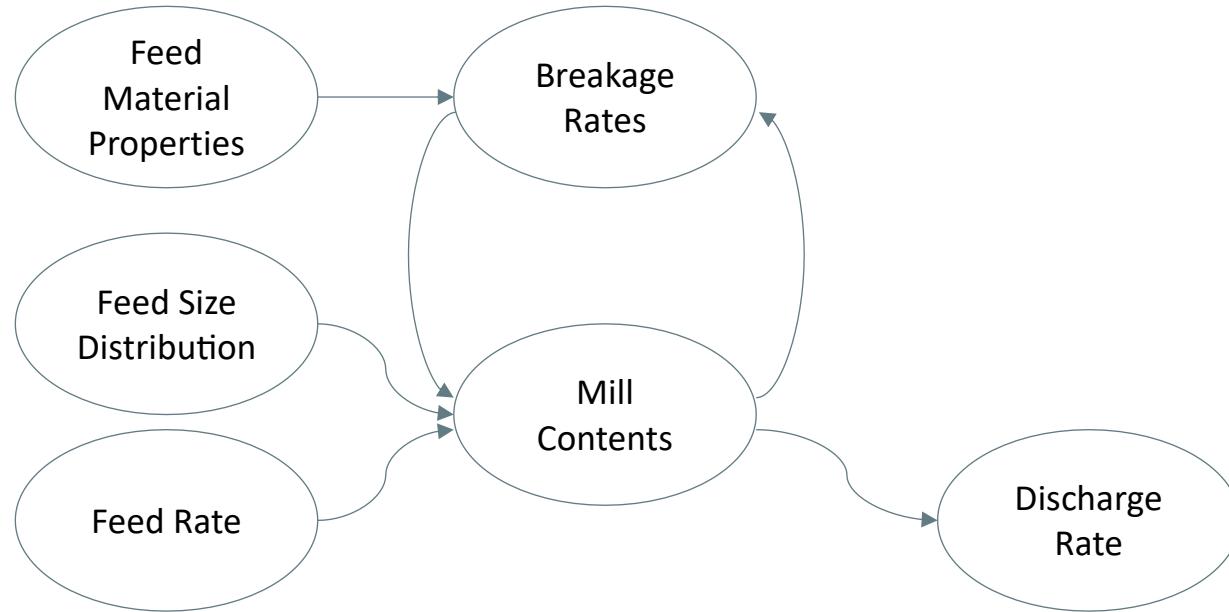
Complex Process With Unstable, Non-Linear Dynamics

Process Characteristics



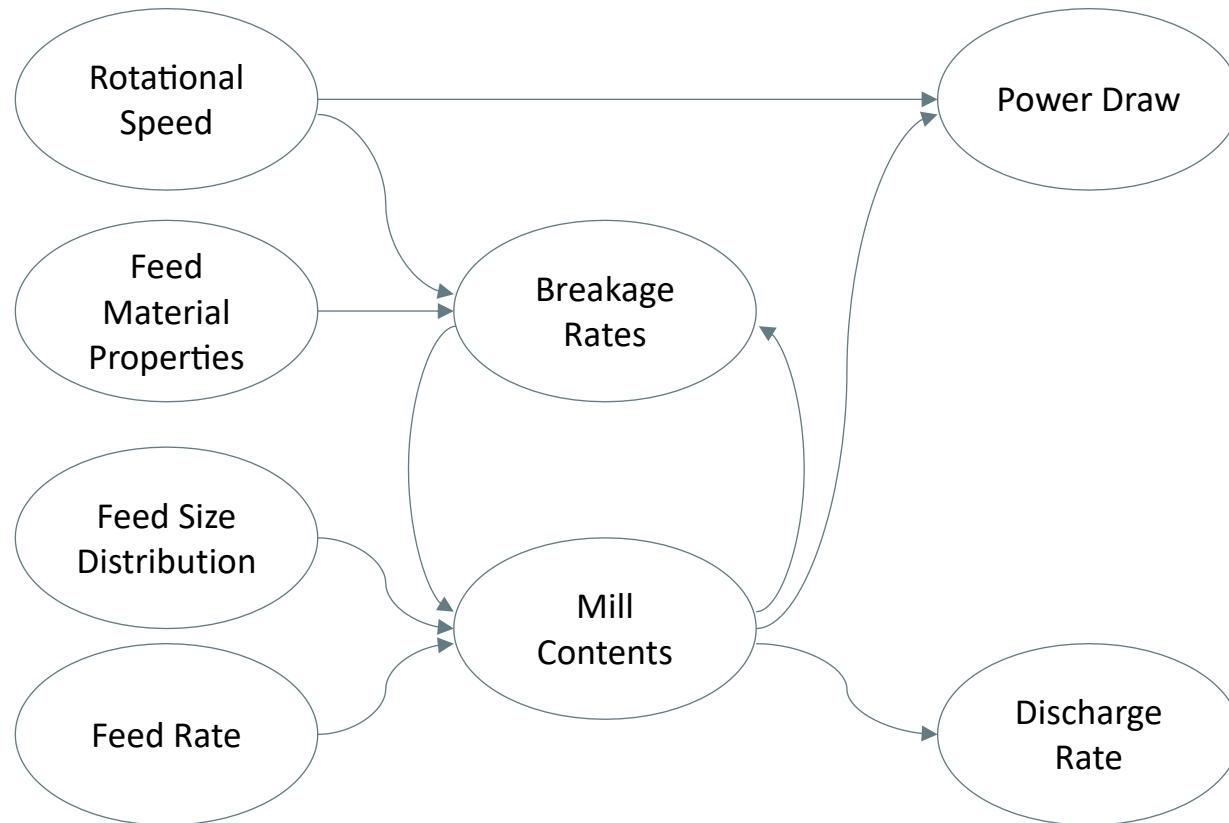
Mill Filling And Speed Have A Significant Effect On Grind, Throughput And Power Consumption

System Dynamics



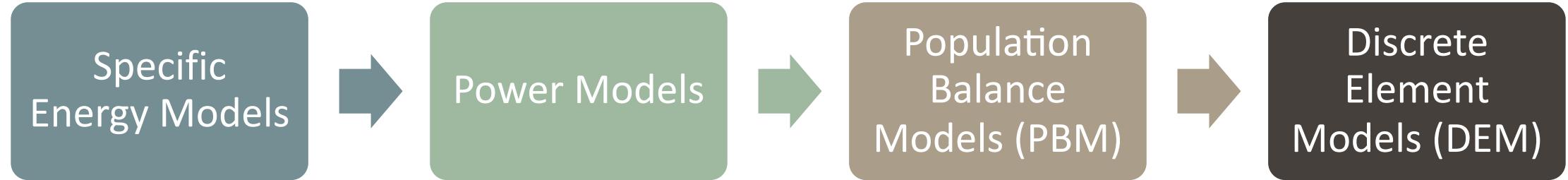
Interactive Effects Between Mill Contents And Breakage Rates

System Dynamics



Interactive Effects Between Mill Contents And Breakage Rates

Process Simulation Models

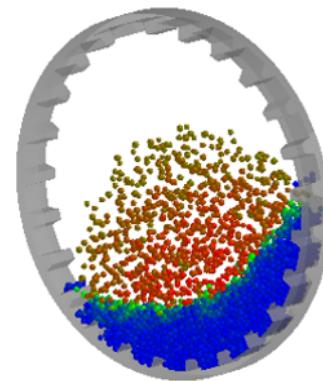


Bond Work Index
(kWh/t)

$P = f(\text{dimensions, ore, speed, ball size, rock size})$



$$\frac{df_i}{dt} = -S_i f_i + \sum_{j=i-1}^1 b_{ij} S_j f_j$$



Process Simulation Models Have Evolved From Simple Specific Energy Models To Very Sophisticated DEM Models

Process Simulation Models

Population Balance Model (PBM)

$$\mathbf{p} = \mathbf{D}\mathbf{f}$$

where

$$\mathbf{D} = \mathbf{B}\mathbf{S} + \mathbf{I} - \mathbf{S}$$

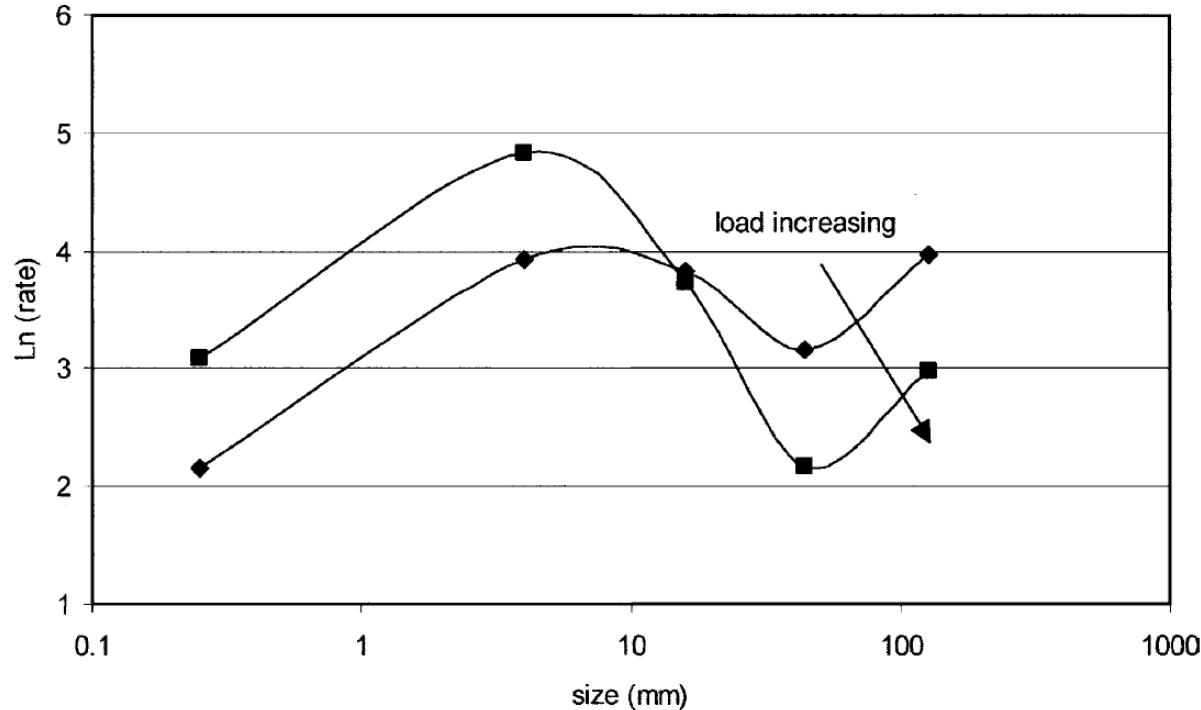
\mathbf{p} is the product vector, \mathbf{f} the feed vector, \mathbf{B} the breakage matrix, \mathbf{I} the unit matrix, \mathbf{S} the selection matrix; this can be illustrated by considering four size intervals as an example, as follows,

$$\begin{bmatrix} w_1(1) \\ w_2(1) \\ w_3(1) \\ w_4(1) \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 \\ b_{31} & b_{32} & b_{33} & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} s_1 & 0 & 0 & 0 \\ 0 & s_2 & 0 & 0 \\ 0 & 0 & s_3 & 0 \\ 0 & 0 & 0 & s_4 \end{bmatrix} \begin{bmatrix} w_1(0) \\ w_2(0) \\ w_3(0) \\ w_4(0) \end{bmatrix} + \left\{ \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} - \begin{bmatrix} s_1 & 0 & 0 & 0 \\ 0 & s_2 & 0 & 0 \\ 0 & 0 & s_3 & 0 \\ 0 & 0 & 0 & s_4 \end{bmatrix} \right\} \begin{bmatrix} w_1(0) \\ w_2(0) \\ w_3(0) \\ w_4(0) \end{bmatrix}$$

Austin (1971)

The Population Balance Model Is A Linear Matrix Model Based On Breakage Probabilities Of Particles In Discrete Size Intervals

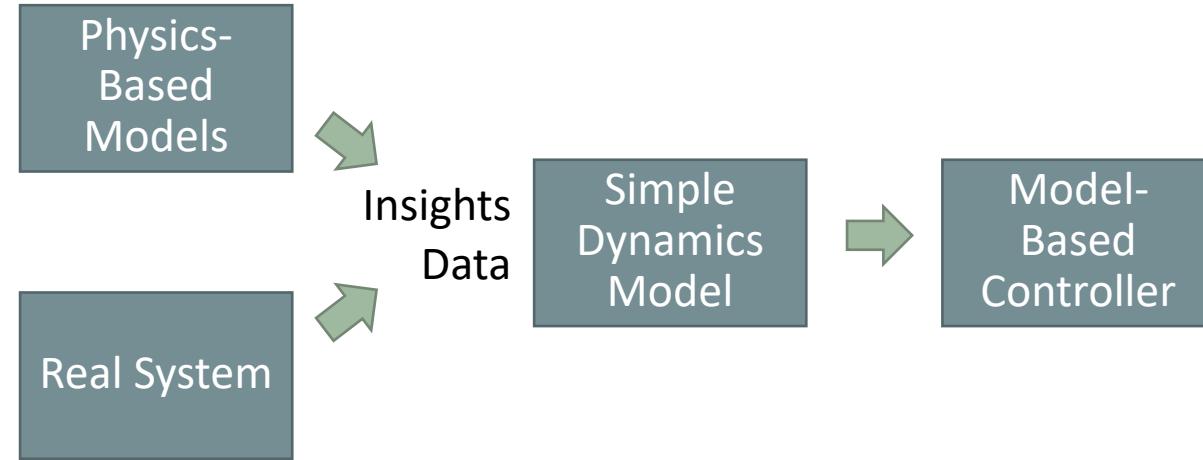
Process Characteristics



Morrell (2004)

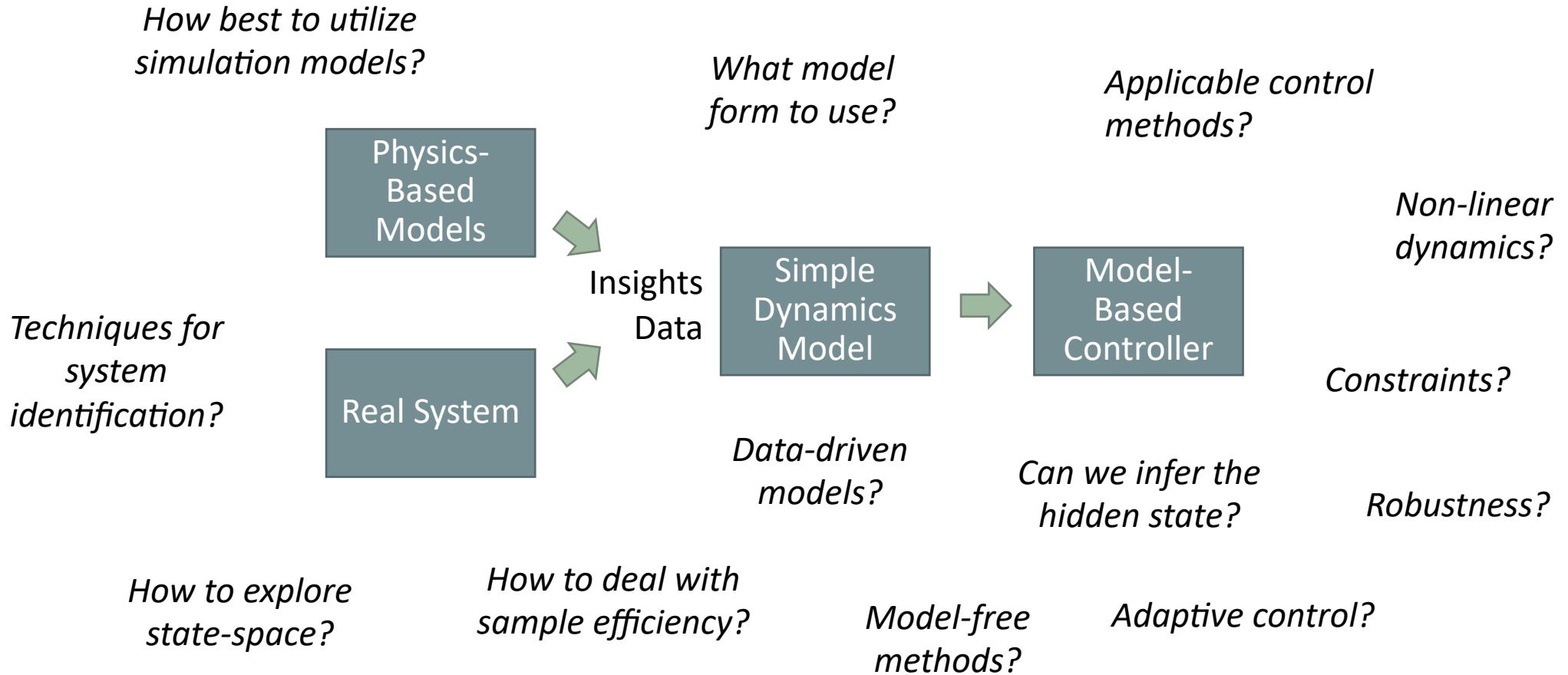
It Is Possible To Fit Simple, Parameterized PBM Models To Empirical Data

Our Proposed Approach



**Hybrid Data-Driven / Model-Based Approach Utilizing Physics-Based Simulation
Models Where Appropriate**

Questions, Comments, Ideas...



Thank You

Bill Tubbs

UBC School of Mining Engineering

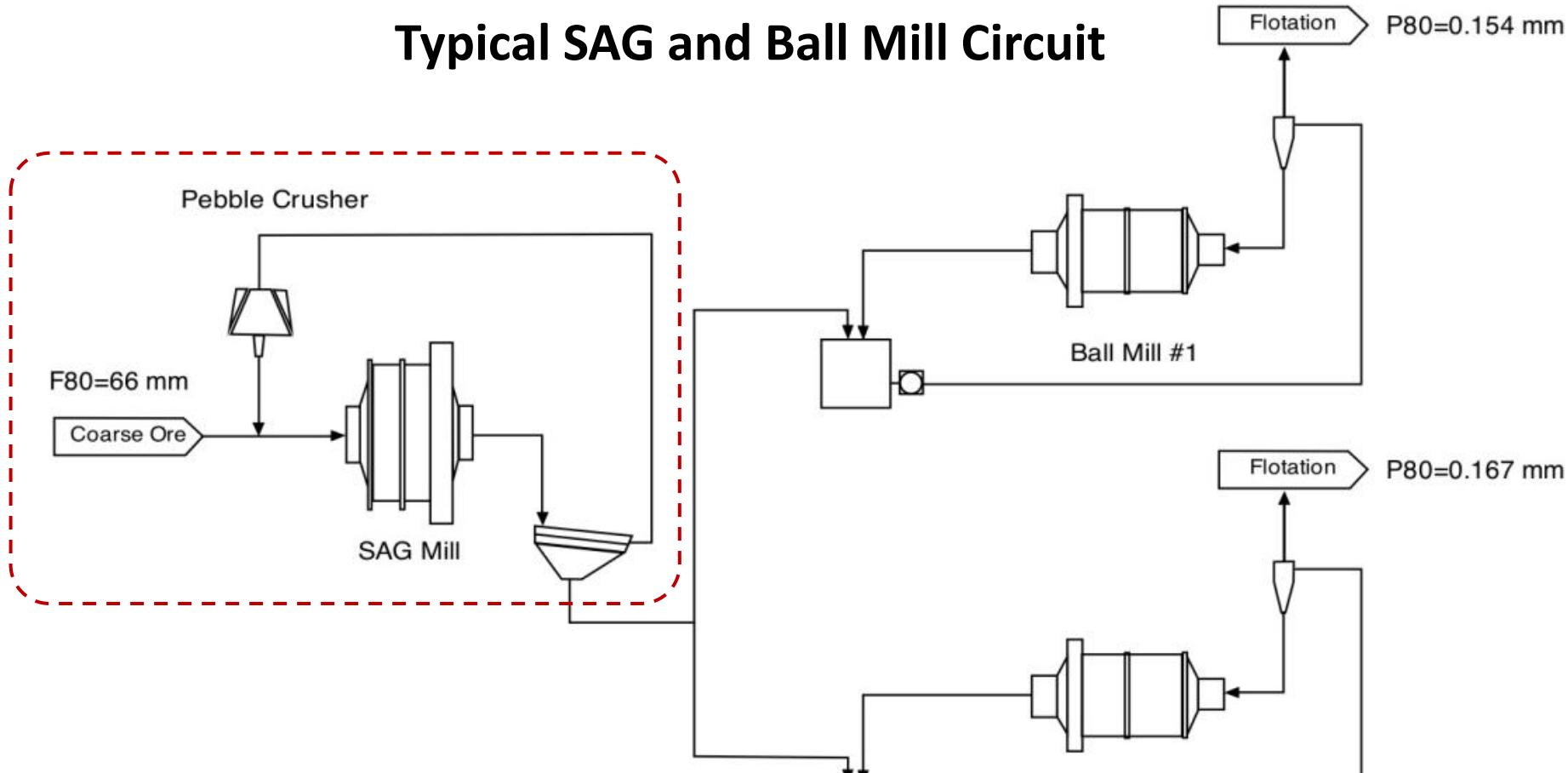
bill.tubbs@me.com

+1 (778) 378 6539

References

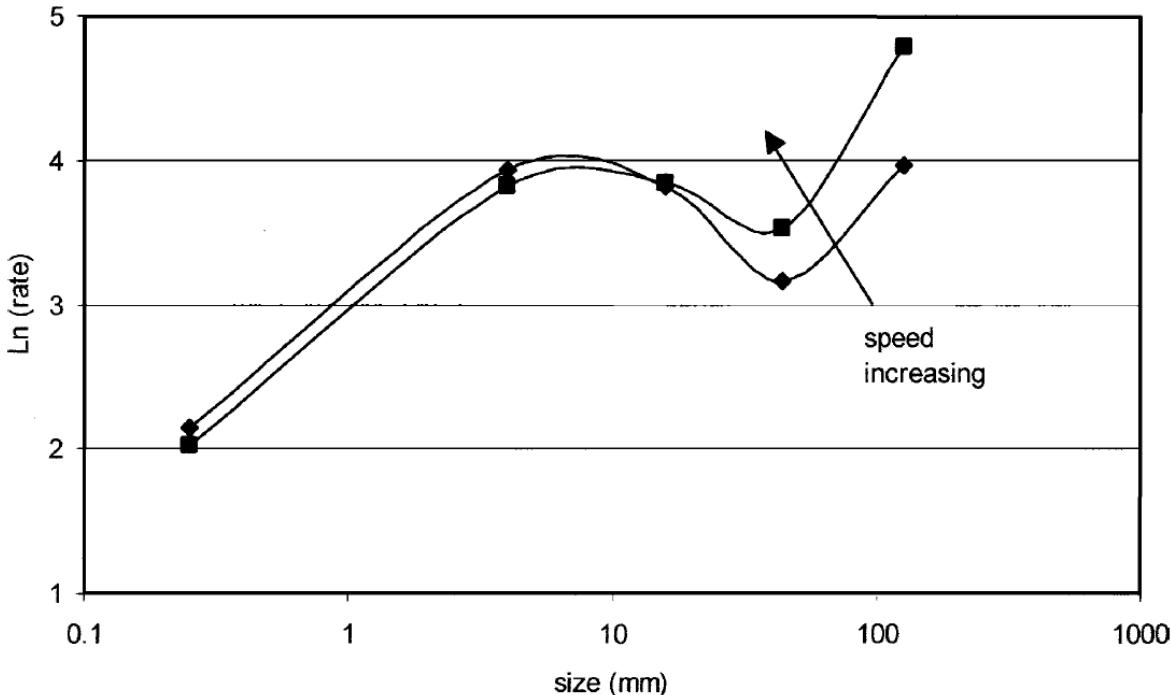
- Austin, L. G. (1971). Introduction to the Mathematical Description of Grinding as a Rate Process. *Powder Technology*.
- McClure, K. S., & Gopaluni, R. B. (2015). Overload detection in semi-autogenous grinding: A nonlinear process monitoring approach. *IFAC-PapersOnLine*, 28(8), 960–965.
<https://doi.org/10.1016/j.ifacol.2015.09.094>
- Morrell, S. (2004). A new autogenous and semi-autogenous mill model for scale-up, design and optimisation. *Minerals Engineering*, 17(3), 437–445.
<https://doi.org/10.1016/j.mineng.2003.10.013>
- Powell, M. S., van der Westhuizen, A. P., & Mainza, A. N. (2009). Applying grindcurves to mill operation and optimisation. *Minerals Engineering*, 22(7–8), 625–632.
<https://doi.org/10.1016/j.mineng.2009.01.008>

Background



SAG Mill Is The First Stage Of The Grinding Process And Experiences The Most Variability Due To Unobservable Changes In Ore Feed Properties

Process Characteristics



Morrell (2004)

Empirical Work From Pilot-Scale And Full-Scale Mills Provides Some Insights

Good / Relevant Books?

- Multivariable Feedback Control Analysis and Design
Skogestad & Postlethwaite (2001)
- Practical Grey-box Process Identification
Bohlin (2006)
- Adaptive Control: 2nd Edition
Åström & Wittenmar (2008)
- Optimization-Based Control
Murray (2009)
- Advanced Control and Supervision of Mineral Processing Plants
Sbárbaro & del Villar (2010)
- Feedback Systems
Åström & Murray (2011)
- Approximate Dynamic Programming: Solving the Curses of Dimensionality
Powell (2011)
- Adaptive Control: Algorithms, Analysis and Applications
Landau, Lozano, M'Saad & Karimi (2011)
- Dynamic Optimization
Poulsen (2012)
- Dynamic Programming and Optimal Control – Vols I & II
Bertsekas (2017, 2012)
- Predictive Control for Linear and Hybrid Systems
Borrelli, Bemporad, & Lucca (2018)
- Reinforcement Learning for Optimal Feedback Control
Kamalapurkar, Walters, Rosenfeld, & Dixon (2018)
- Linear Stochastic Systems
Peter Caines (2018)
- Reinforcement Learning And Optimal Control
Bertsekas (2019)
- Data-Driven Science and Engineering
Brunton & Kutz (2019)
- Neural Approximations for Optimal Control and Decision
Zoppoli, Sanguineti, Gnecco, & Parisini (2020)
- Intelligent Optimal Adaptive Control for Mechatronic Systems
Szuster & Hendzel (2020)