System Dynamics Approach to Tailings Management Simulation

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ABSTRACT: Tailings Management System (TMS) consists of a web of inter-related sub-systems across disciplinary and organizational boundaries. Conventional predictive models simulate physical processes in each discipline with great details. In contrast, simulation based on System Dynamics (SD) focuses on overall behavior of the system over time rather than the typical mechanistic predictions seen in conventional numerical models. SD technique has been widely used in the field of business, ecology, public health, and environmental studies. However, despite the adoption of various SD-based tools in mine water balance and water quality studies, the identification and formulation of causal loop diagrams and feedback structures are rarely practiced in the management of tailings and mine waste. This paper builds on the foundation of a previously developed dynamic simulation tool, Tailings Management Simulator (TMSim) to demonstrate how SD can be used as a framework for inter-disciplinary collaboration and stakeholder communication. Advantages and limitation of SD-based modeling approach will also be discussed.

1 INTRODUCTION

This paper provides an overview of the SD philosophy and how it can be applied in the tailings management context. SD-based modelling process consists of two major parts: qualitative stage and quantitative stage. The paper will focus on the qualitative process while serving as a companion paper to future modeling of soil water dynamics between reclamation covers and underlying tailings substrate.

1.1 *History of System Dynamics*

Originated from the development of feedback control mechanisms for military radars and gun mounts during World War II (Forrester, 1994), System Dynamics is a modelling technique that deals with complex inter-relationships between components within a system or multiple systems. Jay Forrester first applied the methodology in the mid-1950s to the field of business and operations research at the newly created Sloan School of Management at MIT. The first application of SD was a dynamic model, created in late 1950s, to explain poor business performance at General Electric where the employment instability was later discovered to come from internal structures rather than external forces such as economic cycles. In the 1970s, the use of SD gradually shifted from business modelling to urban planning due to the proliferation of low-cost housing initiatives. Over the years, the application of SD has found its way into a variety of fields such as public health, ecology and engineering. (Lane and Sterman, 2017). Today, SD has become a full-fledged academic field so matured that an association named System Dynamics Society and its affiliated academic journal, System Dynamics Review, are solely dedicated to its advancement and promotion.

1.2 *The Big Picture*

Despite its wide applications in business and social sciences, SD has not been widely used in tailings management and mine closure planning. Based on a preliminary keyword review of the bibliography database in System Dynamics Journal, Table 1 showed that only 12% of the total articles in the bibliography database from System Dynamics Society is related to technical fields most relevant to the mining industry. A quick search in other literatures has also yielded very few applications of SD in mining-related fields. Li and Simonovic (2002) successfully used SD to model hydrological processes in groundwater flow. Subsequently, Elshorbagy et al (2005) expanded the SD approach to study flow regime in un-saturated soil cover. More recently, King et al (2017) adopted SD in the evaluation of hydro-power dam safety from a system perspective. Despite potential publication bias in the System Dynamics Review journal, the mining industry at large and certainly niches like tailings and closure management may have benefited very little from this modelling paradigm.

The lack of case studies related to SD in tailings management can be attributed to the unique gap between numerical models and our mental models. Conventional numerical models are based on extensive experimental and empirical evidence. In contrast, mental models are built upon heuristics and intuition. In Figure 1, different types of models are located inside an inverted triangle formed by three axes of scale. The diagram puts the traditional numerical models at the bottom since they provide the foundation on which other types of models are built. At the top of the inverted triangle are the mental and conceptual models, which strive for simplicity and maximum degree of horizontal integration. In the middle of the graph, the intermediate models strive for balance between breadth and comprehensiveness.

Ford (2010) argued that to study climate change, SD models are the most powerful when designed to fit in the conceptual model category at the top. For topics as broad as climate change and evolutionary ecology, maximum horizontal integration across different disciplines is not only productive but sometimes also necessary. However, over-simplification and absence of key physical processes in a model will inevitably pose challenges during calibration and validation process. Furthermore, endogenous variables in climate systems such as precipitation and daily temperatures become exogenous in a tailings management context due to the much smaller system boundary. Therefore, SD-based models in tailings management should aim for the middle ground between conceptual models and traditional numerical models.

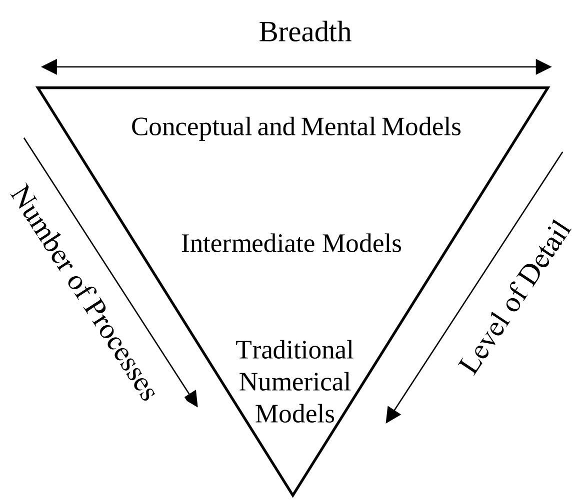


Figure 1. Classification of models

Table 1. Keyword search of System Dynamics Review bibliography database.

Keyword	Number of Articles	Proportion*
Mining	88	<1%
Water	972	8%
Construction	500	4%
Dam	17	<1%

*Based on a total number of 12,412 articles.

2 SD MODELLING PROCESS

2.1 *Qualitative Stage*

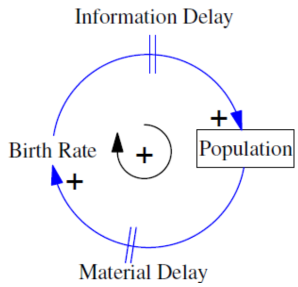
Stocks and flows, feedback structures are the three basic building blocks of any SD-based models. Stocks are state variables that track accumulation of quantities at any given time. Flows are variables that add or subtract quantities per unit of time step. Feedback structures are closed-form relationships that either reinforce or balance each other. Auxiliary variables in the form of mathematical equations are often required to explain Flows.

The qualitative stage of model development involves the following steps: i) familiarization with the system and background studies; ii) construction of specific questions that need to be answered by the model; iii) identification of variables, stocks and flows; iv) formulation of causal loop diagrams; and v) iterative revision of causal loop diagrams through learning, debate and discussion. It should be noted that, though anything qualitative tends to be perceived as being conceptual, the qualitative stage in SD modelling is a rigorous process with its own set of syntax, clear-defined rules and best practices. During this stage of model development, general patterns are more important than precise numbers (Ford, 2010).

Feedback structures are represented by causal loop diagrams which are drawn by the Vensim software in this paper. Figure 2 is a popular case study used in many SD literature to explain the basics of causal loop diagrams. Here, population is treated as a stock. Variables are connected by one-way arrows which represent causal relationships. Either positive (+) or negative (-) polarity is assigned to the arrowhead based on how the dependent variable changes in response to changes in the independent variables. Positive causal link means that the linked variables change in the same direction. All else being equal, a higher birth rate will increase population which in turn drives up the birth rate. Negative causal link means that variables change in the opposite direction. A higher death rate will decrease population which in turn reduces death rate. It should be noted that, as a good practice, polarity is assigned by testing the effect of positive polarity on variables at the arrowhead.

If the number of negative polarities in a loop is odd, the feedback loop is classified as negative. If the number of negative polarities is even, the feedback loop is identified as positive. Negative feedback loop balances the system while positive feedback loop gives rise to run-away behavior or amplified system response to any changes in variables (Richardson, 1997).

In Figure 2, the parallel lines at the top and bottom of the loop denote the concept of delay. There are two types of delay: material delay and information delay. For the material delay, the effect of increasing population will not be reflected in the birth rate since family formation and pregnancy take time. For the information delay, even though the effect of rising birth rate is instantaneously reflected in the population, modelers will not be aware of this information due to time interval between censuses. The same rationale can also be applied to the delay effect shown in Figure 2b.



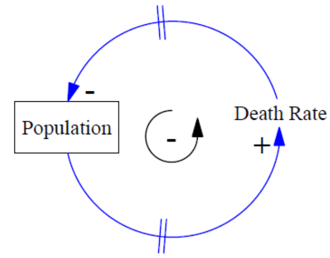


Figure 2. a) Causal loop diagram for population growth b) Causal loop diagram for population decline

The methodology used for constructing Figure 2a and 2b can be applied to examining the one-dimensional consolidation behavior of foundation soil under a rising tailings storage facility. In Figure 3, excess pore pressure is modelled as a stock element with construction rate as inflow and dissipation rate as outflow. Assuming that Darcy's Law is valid and that the principle stress in the foundation soil can be approximated by the vertical stress, an increase in construction rate will trigger a series of chain reactions and lead to a negative feedback structure, which makes sense since the consolidation process brings the system back into balance. The counter-clockwise loop symbol is also given a name to communicate the major theme of the feedback structure. Alternatively, a numeric value can be assigned to keep track of multiple feedback loops.

Variables outside the feedback loop are considered exogenous while those from inside are considered endogenous. In this case, construction rate, hydrostatic pore pressure and existing total stress are all considered exogenous or external to the system. Exogenous variables can become endogenous and vice versa depending on how the boundary of the system changes. For example, construction rate becomes endogenous when additional feedback loops are used to incorporate the observational method and contingency plans. It is the endogenous variables that give rise to interesting behaviors in the system (Richardson, 2011).

The causal loop diagram in Figure 3 does not contain enough information for quantitative modelling since additional feedbacks, delays and auxiliary variables are absent. Spatial arrangement, level of confining stress, principle stress rotation, and in-situ soil properties are also not explicitly considered in Figure 3. However, the systematic process of creating the diagram builds a robust foundation on which further revision of the model can be communicated across disciplinary boundaries.

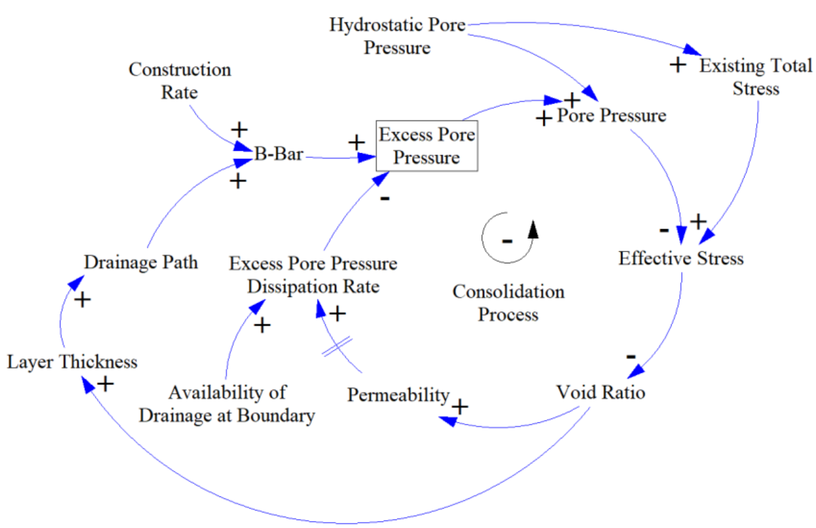


Figure 3. Causal loop diagram for consolidation of foundation layer under fully saturated condition (Zheng and Beier, 2018)

2.2 *Quantitative Stage*

The quantitative stage of SD consists of the following major steps: i) conversion of causal loop diagrams to runnable models; ii) parameter estimation; iii) sensitivity analysis; iv) analysis of varying parameter input and model structures; and v) continued model maintenance based on new information and insights. The quantitative process in SD is similar to that of conventional numerical modelling except in a few areas that require new ways of thinking. These areas of differences are discussed in Section 2.3 and further addressed in Section 3.1 and 3.2. Case studies and SD-based tailings management models will be presented in a separate paper.

2.3 *Model Maintenance*

SD models are not pre-made packages off the shelf. Building models from scratch is the norm rather than the exception in SD modelling (Homer, 1996). Since it is possible to incorporate tentative knowledge and personal beliefs in SD models, continuous improvement of the model is necessary, especially when key parameters transition from being soft to hard as a result of new data becoming available.

Mine plans and tailings plans keep evolving through multiple feedback structures. At the beginning of mine development, mine planners provide input parameters to tailings planners in a one-way manner. Over time, mine plan will have to be continuously adjusted as the performance of tailings system becomes available and lessons-learned is shared. This dynamic nature of planning cycles requires constant questioning of underlying assumptions in SD models.

3 WHY SYSTEM DYNAMICS?

3.1 *Advantages and Benefits*

a) Transparency

In a SD simulation environment, all elements and functional relationships are exposed, visual and transparent through causal loop diagrams and stock-and-flow figures. Modelers and users can also explore the underlying empirical relationships and numerical schemes that are used to explain inter-relationships between elements. There should be no black boxes and hidden components in a SD simulation environment (Nicolson et al, 2002). In Figure 4, additional visualization is used in GoldSim to enhance clarity for dynamically simulating volumes of Fluid Fine Tailings (FFT), further demonstrating the communicative power of SD.

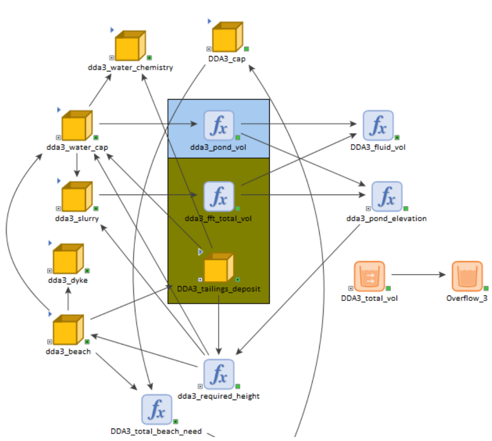


Figure 4. Elements of a sub-model in GoldSim (Modified from Beier, 2015)

b) Flexibility and Expandability

As part of top-down approach, simplified "child" models can first be developed prior to creating time-consuming larger models. The nature of object-oriented programming allows for scalability of those "child" model elements, saving time and preventing accumulation of errors in the future. This is particularly true for spatial components since SD-based tools can intrinsically handle time but not space. In case greater spatial accuracy is required, SD model can be easily expanded if elements in each "child" models follow the same structure and naming convention.

Figure 5 shows a consolidation "child" model for tailings deposits developed in the GoldSim software. In Figure 5a, all elements of the calculation process and their respective influence directions are exposed and visible to the user. The numerical scheme is linearized based on an explicit, non-iterative finite difference method. In Figure 5b, each red-colored box or container denotes a discretized layer which stores the elements in Figure 5a with identical format and naming conventions. A total of 12 containers were specified for this model. However, should greater accuracy be needed, the user can easily add more containers by duplication without creating new mathematical relationships.

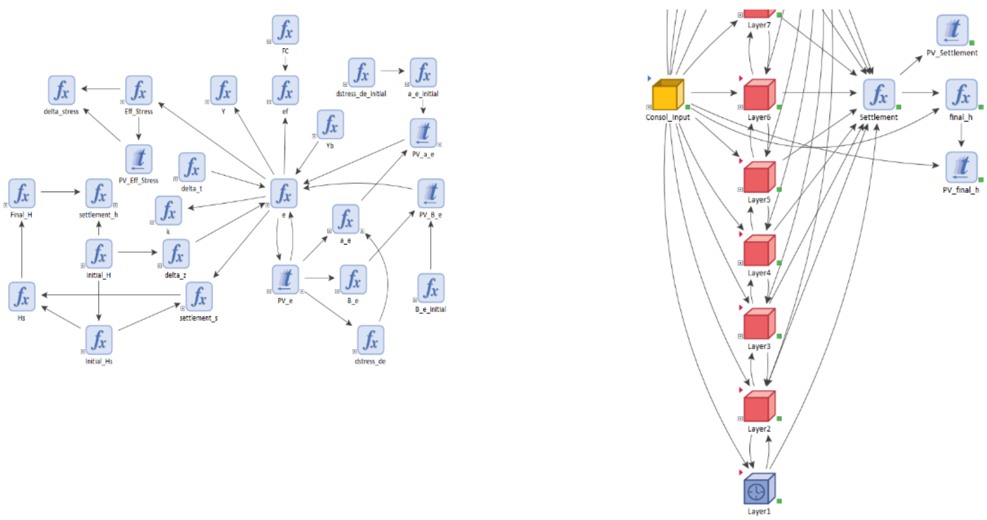


Figure 5. a) Exposed components of the "child" consolidation module; b) Parental setup of all the "child" consolidation modules with 7 spatial layers visible. (Zheng and Beier, 2018)

The causal loop diagram in Figure 6 is constructed using the methodology described in Section 2.1. As the name of the feedback loop suggests, the diagram focuses on 1D un-saturated flow mechanism in a soil layer. Figure 6 may be sufficient if the goal is to understand the run-away behavior of the system under climatic forces. However, if the objective of the model is to evaluate the state of water storage and soil water content over time, Figure 6 needs to be expanded to include additional pieces of physics.

As shown in Figure 7, flexibility and expandability inherent in causal loop diagrams allow for the incorporation of evapotranspiration process and effect of volume change to the unsaturated flow mechanism. As expected, evapotranspiration is a negative feedback loop, providing checks and balances to regulate the run-away behavior of unsaturated flow and volume change. There are still rooms for expansion since Figure 7 assumes the absence of bottom boundary conditions, surface run-off and inter-flow between adjacent layers.

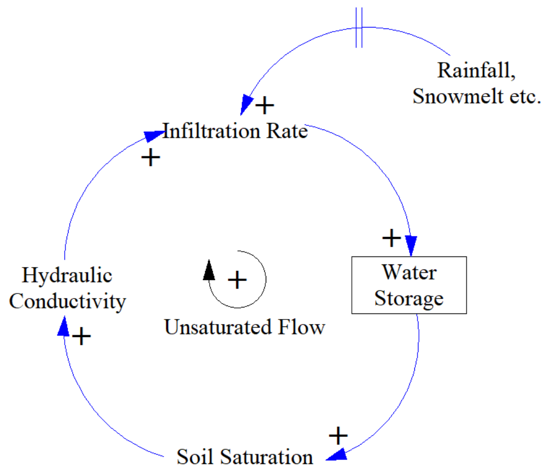


Figure 6. Causal loop diagram for un-saturated flow in soil cover (Modified from Elshorbagy et al, 2005).

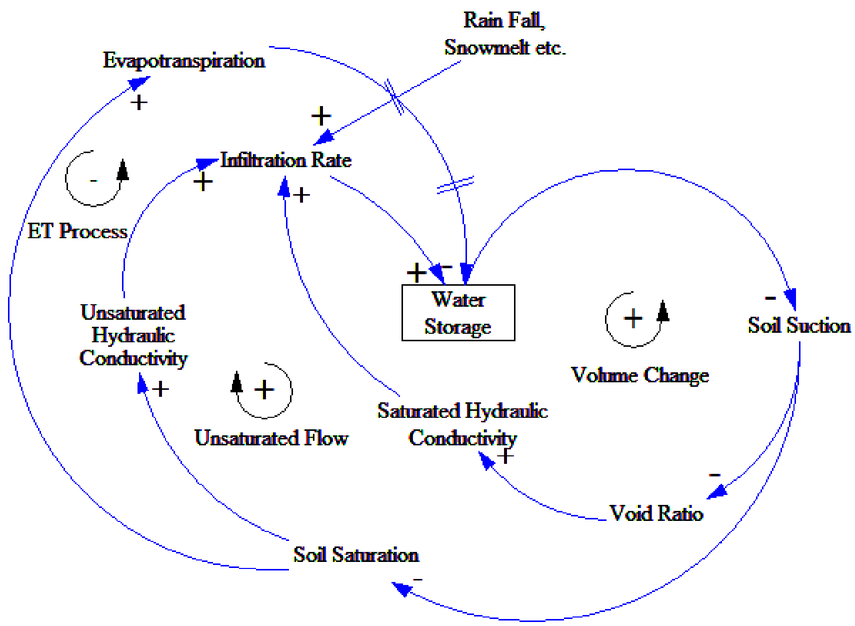


Figure 7. Expanded causal loop diagram from Figure 6.

c) *Stakeholder Participation*

Due to the extensive qualitative process prior to quantification of model parameters, the modelling process itself, rather than the end-product, offers the greatest insights. This view is supported by publications on the philosophy of SD modelling (Richmond, 1993; Forrestoer, 1994; Sternman, 1994 and Meadows, 2008) as well as on case histories of SD (Hovmand, 2014 and ElSawah et al, 2017). Beier (2015) also echoed the same view in the conclusion for simulating the Cross-Flow Filtration (CFF) tailings dewatering technology that failed simulation runs and the process of gathering input data itself provided insights into underlying mine planning assumptions.

Hovmand (2014) showed that stakeholders without in-depth knowledge of differential equations are able to contribute to model conceptualization, formulation and simulation through causal loop diagramming exercises in a group workshop setting. Minimum expertise in coding is required for participants to actively engage in the modelling process. In fact, this type of modelling workshop is feasible even without any basic knowledge of SD from the participants.

Hager et al (2015) described a case study where researchers attempted to use qualitative measures from SD to equip small-scale village farmers in Zambia with short-term and long-term strategies to increase their food security and economic stability. In addition to the tactical objectives, a more strategic goal of the study was to improve the shared learning experiences in preparation for changing environment and adaptive policies. In Figure 8, stock and flow elements were represented by tangible objects familiar to the village farmers. Variable names were simply written on the white board. Model facilitators used water glasses to show effects of changing variables and devised intuitive terms such as "draining the glasses" and "filling the glasses". The end results were encouraging, according to Hager et al (2015), despite participants' lack of formal training in SD.

In the tailings planning context, participatory modelling is expected to be less challenging than the above case study given the multi-disciplinary nature of the mining industry and a well-trained workforce at major mining operations. Causal loop diagram can be an effective communication tool through which different disciplines can communicate with each other under a formalized framework.

Figure 8. Community-based modelling workshop in Zambia (Hager et al, 2015)

d) Structural Sensitivity

Numerical sensitivity analysis studies the impact of varying specific parameter input with other parameters being held constant. In contrast, the emphasis of structural sensitivity is no longer the variation of numerical values but instead the structural uncertainty and behavioral assumptions of the model. As Ford (2010) pointed out, both input and output can change if the fundamental structure of the model is altered. For example, a different model time step is required if the dominant groundwater transport mechanism changes from advection-based to diffusion-based process. Sterman (2004) also recommends the modeler to examine the sensitivity of results to alternative structural assumptions, such as changing key performance indicators and how boundary conditions of the system are treated.

e) The "Intangibles"

TMS is a complex system of inter-related "intangible" components outside the technical realms. Primary organizational and human components of TMS consist of: in-house operation staff, Engineer-of-Records, Independent Technical Review Board, consultants, research institutes, advisory associations, regulatory bodies and community stakeholders (MAC, 2017). In addition to the adoption of Best Available Technology (BAT) and Best Available Practice (BAP), understanding the dynamic interaction between those organizational and human components plays an equally important role in successfully managing TMS.

The qualitative and quantitative framework of SD provide opportunities for integration between the construction side and design aspects of TMS. Figure 9 illustrated a causal loop diagram for a typical scenario related to construction Quality Control and Quality Assurance (QA/QC) of a tailings storage facility. For simplicity, only three feedback structures most critical to the process were shown, and it should be noted that they do not depict a complete picture of the construction QA/QC process. As described in Section 2.1, each feedback loop is classified as either positive or negative and given a name to reflect its major theme.

For large-scale tailings dams that stretch over several kilometers in length, it is not uncommon to open multiple work fronts far apart and construct the dam structure simultaneously from different locations. It is also desirable, from a financial perspective, to maintain high rate of construction to meet aggressive deadlines and save on equipment and labor costs.

In Figure 9, the original student-assignment model from Sterman (2004) was revised to better fit in the tailings construction context. At a fixed staffing level, backlogs are created by an increase in the number of work fronts and construction rate. Mathematically, "Tasks Backlog" is equal to rate of new tasks subtracted by "Task Completion Rate". Work pressure depends on the number of backlogged tasks and inspection interval assigned to each task. The shorter the time interval between inspection, the longer work hours are required to complete all the QA/QC tasks.

For management, the first intuitive reaction to increasing backlogs is to demand overtime and longer work hours. The positive feedback loop "QA/QC Staff Burnout" operates as a vicious cycle – increasing work hours to combat backlogs leads to more backlogs being generated.

The negative loop in "Staff Feedback" balances the vicious cycle in "Staff Burnout". As work pressure is increased, QA/QC staff may submit additional requests for extension of time between each inspection. In response, construction managers will extend inspection intervals based on the frequency of requests from QA/QC staff. With more time to travel between each work front, QA/QC staff now has less work pressure, which will work through the positive feedback loop to reduce the backlog of tasks.

The negative feedback loop of "Corner Cutting" also balances the vicious cycle in "Staff Burnout". One way to reduce backlogs is to spend less effort on each task, which in turn increases task completion rate. Since both "Productivity" and "Efforts Devoted to Each Task" work together to affect "Task Completion Rate", their combined effect on "Tasks Backlog" depends on which feedback loop structure would dominate the other over time.

Elements from both design and construction can be combined into one causal loop diagram through shared variables (i.e. construction rate). A more extensive causal loop diagram is possible by incorporating more feedback processes such as the observational method and budget control. The combination of causal loop diagrams from different perspectives promotes inter-disciplinary understanding. However, as causal loops are combined and expanded, it is important to strike the right balance between over-simplification and over-complexity of the system boundary.

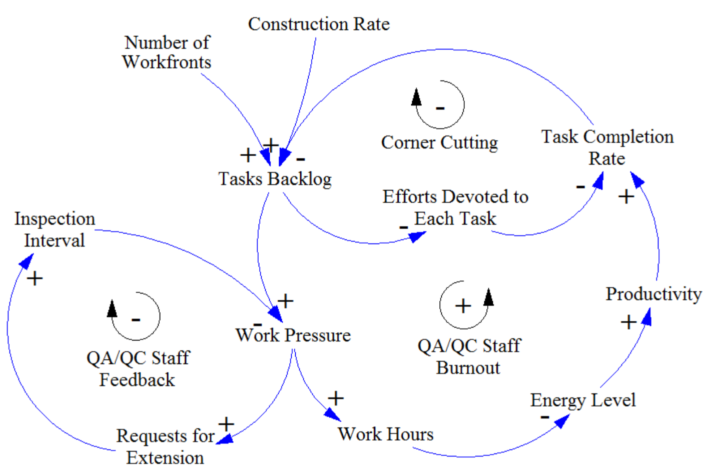


Figure 9. Causal loop diagram for staff fatigue and burnout (Modified from Sterman, 2004)

3.2 *Discussions*

a) Predictive Power

SD models are constructed to help us gain a big-picture understanding of system behaviors and why they follow certain patterns (Forrester, 1980). The process of simplification and linearization of key physical processes inevitably reduce their predictive powers in terms of absolute numeric values. SD models may provide satisfactory prediction in exchange for larger model size and increased computational time. However, since SD models are lumped models that only provide the average state of the system, traditional numerical models are better suited for precise prediction over time.

On the other hand, predictive models focus on a singular objective that is to provide the most accurate forecast of the future state of the system. Reconciling the difference between predictive models and SD-based models continues to be a challenge partly due to heavy emphasis on discipline-based, narrowly-defined numerical modelling methods taught in the engineering curriculum (Saito et al, 2007). Furthermore, SD models are often misunderstood as predictive models, further deepening the suspicion from end users (Ford, 2010).

b) Validation

Validation of predictive models is straightforward. Matching model results with historical and experimental data gives confidence in the model provided that the same underlying assumptions and boundary conditions are used during the validation process.

Validation of SD-based models is similar to that of predictive models based on matching historical behavior and measured data if available (Elshorbagy et al, 2005 and Huang et al, 2011). Difficulties arise when little to no measured data exists, as in the case of farm villagers in Zambia in Figure 8 and staff fatigue and burnout model in Figure 9. In this case, alternative validation approaches must be adopted. Various practitioners and theorists of SD have advocated for a soft approach to validation: building confidence in the model through debate, education, critique and qualitatively matching behaviors based on expert opinion and well-established fundament physical processes. Adding more controversy is the notion that validation and verification are impossible, and that all models are ultimately wrong since models are considered simplifications of the reality (Forrester, 1961). Sterman (2004) noted that validation in a SD context is an iterative process where modelers and users continuously question the model's ability to qualitatively replicate expected behavior based on critiques, discussion, known empirical relationships, tentative knowledge and expert opinions. These un-settled validation techniques have become a point of contention and heavy criticisms for the SD modelling paradigm.

c) Causality vs Correlation

Causality should not be confused with correlation. The arrow linking variables and stocks in Causal Loop Diagrams must represent strong causal relationships without ambiguity.

Sometimes, the difference between causality and correlation is obvious. For example, in Alberta, the amount of precipitation correlates well with the level of construction activities. However, higher rate of construction activities is not caused by greater amount of precipitation during summer but instead by the availability of favorable weather condition.

Modelers need to pay close attention to differences between causality and correlation. In tailings dam construction, for instance, it can be tempting to draw a causal link between frequency of dam foundation movement and number of construction workforce. The modeler must critically debate the strength of the causal link by asking what other factors stand in between foundation movement and number of construction workforce. As shown in Figure 10, causality is improved by breaking up the original link and adding another variable that has strong causal polarity to the other two variables.

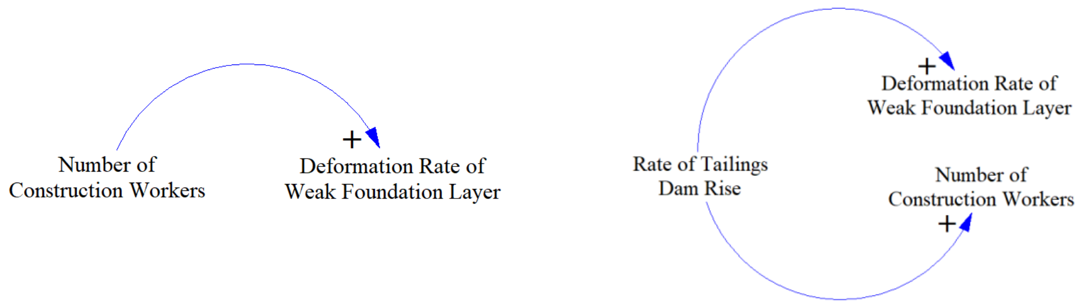


Figure 10. a) Incorrect causality b) Improved causality

d) Resistance vs Over-reliance

When SD is employed in a participatory modeling environment, resistance to adopting SD can come from specialists who tend to concentrate on the detail with which they are most familiar. (Nicolson et al, 2002). To be successful in inter-disciplinary modelling exercises, Cockerill et al (2007) suggested that participants need to have a sense of humility and accept the fact that they need to learn new languages and concepts from other disciplines as well as general principles of SD modeling. Nicolson et al. (2002) further warned that there will be steep learning curves for participants even though they may be experts in their respective fields.

At the other end of the spectrum is over-reliance on SD models which seem to have the ability of integrating multiple disciplines. Limitations in the predictive power of SD models cannot be ignored. Over-emphasis on causal loop diagramming can also erode sound scientific basis and exaggerate the usefulness of conceptual models. Homer (1996) reported an alarming trend that the ease with which causal loop diagrams can be created may have exacerbated the belief that SD is mainly conceptual instead of empirical, and that creativity takes precedence over thoroughness.

4 CONCLUSIONS

SD allows for coupling of multiple processes and systems across disciplinary boundaries. Figure 3 and Figure 9 demonstrated the potential marriage between technical and business models through causal loop diagrams. Figure 6 and Figure 7 showed how SD techniques can be applied to model multiple physical processes that can also interact with each other. Figure 8 provided an example on how a complex model can be communicated and conceptualized by stakeholders without knowledge of differential equations.

Furthermore, the qualitative stage of the SD modeling is a rigorous process with its own syntax, well-established rules, and best practices. The qualitative stage of SD modeling process also emphasizes transparency, simplicity and flexibility. The process of constructing causal loop diagrams provide further insights into the tailings management process and serve as a vehicle for inter-disciplinary communication.

However, causal loop diagrams constructed above are not inclusive and may not contain enough information for subsequent quantitative modeling exercises. As research and stakeholder participation progress, additional causal loop diagrams, variables and processes need to be identified and incorporated. At the same time, redundant components and insignificant processes may be discarded. Historical data and empirical evidence are also required for validation purposes.

5 ACKNOWLEDGEMENTS

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