CALIBRATING SYSTEM DYNAMICS MODELS OF TECHNOLOGY DIFFUSION WITH STRUCTURAL BREAKS: THE CASE OF ANDROID HANDSETS

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Abstract

Diffusion of new technologies has been a major application domain for system dynamics (SD) models. A common assumption when calibrating such SD models is that the key parameters driving diffusion, such as contagion strength, are constant over the duration of analysis. However, particularly in the context of new technology difffusion, these parameters may change over time, sometimes dramatically. This can result in so-called called structural breaks in the diffusion pattern. Calibrating SD models in the presence of structural breaks presents some challenges. We discuss these issues in the context of Android handsets, using quarterly sales data for the period 2009-2012, and referring to specific events in its evolution.

Keywords: Diffusion models, dynamic parameters, calibration, structural break, Android.

1 Introduction

Calibration is a critical part of the System Dynamics (SD) model building process, as it helps build confidence in the validity and usefulness of the model (Forrester & Senge, 1980), (Barlas & Carpenter, 1990), (Sterman, 2000), (Oliva, 2003). It entails tuning the model structure as well as parameters, so that the model-generated behavior is "right for the right reason" (Oliva, 2003 p3). While calibration of model structure involves a process of refutations, negation and qualitative simulation (Barlas, 1996), (Qudrat-Ullah et al., 2009), calibration of parameters requires use of statistical techniques that results in simulated

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behavior mimicking observed behavior closely (Forester & Senge, 1980), (Barlas, 1989), (Sterman, 2000), Oliva (2003).

A common assumption during calibration is that the parameters being calibrated are constant over the period of analysis. However, this assumption can be violated, particularly for new technology diffusion, due to evolution of technology capabilities, changing consumer perceptions and changing regulations. Examples of statistical models of technology adoption with non-stationary model parameters can be found in studies such as Meade and Islam (2006). In the case of SD models of technology diffusion, the presence of non-stationary model parameters raises two issues with respect to calibration. First, the timing of the parameter changes, or break points, needs to be determined. Once these break points are identified, model parameters need to be calibrated to accommodate these breaks.

We examine this problem by specifically modeling the diffusion of Android based mobile handsets, a technology that is about six years old and is still evolving. We first develop an SD diffusion model based on a contagion mechanism. We accommodate changes in the strength of the contagion parameter that determines how rapidly the new technology diffuses. The effect of Apps appears as complementary goods that contribute to network effects. The development of a mobile operating system (MOS) such as Android is marked by a discrete events and a steady stream of incremental enhancements. We accommodate this by allowing breaks to occur in the contagion parameters at specific points in time.

In the next section we trace the history of Android growth and briefly review relevant literature on diffusion of new technology. We then develop a contagion model of Android diffusion using SD. This model is then calibrated in a way that accommodates the presence of structural breaks in the diffusion pattern.

2 Android Mobile Devices

Android is a Linux-based operating system for mobile telephones and tablets developed by the Open Handset Alliance in partnership with Google and other companies (Burgelman et al., 2009). The source code is available under free and open source software licenses. Devices running on Android adhere to the Compatibility Definition Document (CDD). The hardware manufacturer has complete freedom to utilize and customize, and Google does not charge any royalty from the hardware manufacturers for OS distribution rights. The first handset device running on the maiden version of Android OS was launched on 22nd October 2008. Table 1 shows a history of Android handsets for the period 2008-2011 (German, 2011).

Table 1: Changes in Handset Model, Handset Feature and User Satisfaction

Month-Year	Number of Models	Min of User Rating	Min MSRP	Max of Talk time Minute	Min of Weight	Max of Screen Size (Inch)
Oct-08	1	3.50	330	300.00	5.60	3.2
Oct-09	6	2.50	179	385.00	5.70	3.7
Mar-10	12	2.00	100	350.00	4.70	3.1
Nov-10	54	1.00	30	540.00	3.60	3.8
Jul-11	95	2.00	129	624.00	3.88	4.3

It is evident that handset price dropped dramatically and phone features improved significantly. Interestingly, Table 1 shows that User Rating has gone down in the same period. Google search patterns also point to growing usability issues until December 2011

(Google Trends, 2013). In addition to handset attributes, another factor that has contributed to the diffusion of Android handsets is the availability of complementary goods in the form of 'apps' that users can buy from the 'Play Store'. Developers of Android apps enjoy a low barrier-to-entry, but the huge diversity in the combination of different input mechanisms, processor types and screen sizes, has caused difficulty in developing and testing of apps. Coexistence of different Android versions has complicated the situation further.

Google made several changes in the Android play store over time. Some changes were targeted towards handset users, while others, like the release of higher version software development kit (SDK) and Native Development Kit (NDK) were targeted towards developers. In July 2012, Google also made a major overhaul of developer policy (Google Play, 2012) with the aim of improving user experience.

The preceding discussion shows that the evolution of Android platform has been marked by both incremental as well a discrete changes.

3 Modelling Growth of Android Mobile Devices

Diffusion of a new technology typically follows a contagion process that results in an S-shaped growth pattern (Rogers, 1976). Two functions that have been commonly used to approximate this pattern are the Logistic and Gompertz functions (Bass, 1969), (Mahajan and Muller, 1979). Using time series data on Android handset sales (Gartner, 2013) from 2009-2012, we were able to fit the Logistic curve with a Mean Absolute Percentage Error (MAPE) of 13.86% and the Gompertz curve with an MAPE of 10.12%.

For purposes of this paper, the significant point is that these diffusion curves assume that the process underlying the diffusion is stable. Moreover, they lack the ability to explain the mechanics of growth. As discussed earlier, however, technology diffusion processes may not be stable and its contagion parameters may indeed change over time. In the following section we present an SD model of Android diffusion that accommodates the possibility of changes in the contagion parameters during the calibration process.

3.1 A Causal Model of Android Diffusion

Figure 1 presents a causal model of Android diffusion. At the core of diffusion is the basic contagion mechanism (loop L1) and that of market saturation (L2). Loop L3, which connects *Installed Base Android* with *Contag Strength Android* represents a Network Externality effect. The externality effect can be both positive (a growing user group increases the value of adopting an Android hand set) and negative (growth in user base creates more opportunities for dissatisfied users through negative word of mouth and congestion). Loop L4 represents the response of handset manufacturers to growing *Adoption Rate Android*. The impact can also be both positive (growing sales brings in new entrants, lowering price and inducing more people to adopt) and negative (quality of low priced handsets fail to satisfy market and drives away potential adopters).

The model of Figure 1 is converted into a stock-flow simulation model by using appropriate policy equations that drive the growth. Two important equations that the simulation model would have are one for *Adoption Rate Android* and the other for *Contag Strength Android*.

Since diffusion is based on a contagion process, *Adoption Rate Android* can be modeled based on standard Infection Rate equation (Sterman 2000) and be written as:

$$AR_{android} = CS_{android} * IB_{android} * \frac{PA_{MOS}}{PA_{MOS} + IB_{android} + IB_{Other}} \tag{1}$$

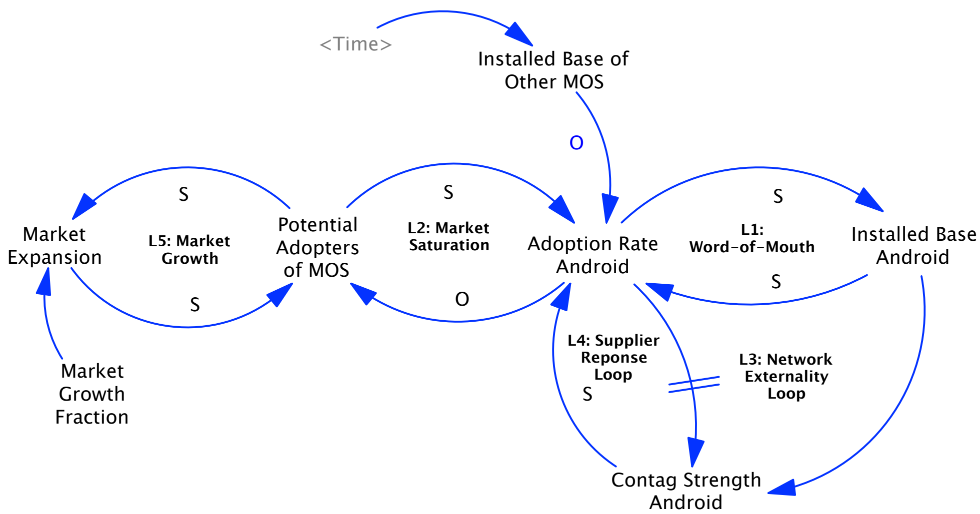

Figure 1: Causal Model used for Calibration of Android Diffusion

Where, $AR_{android}$ is *Adoption Rate Android*, $CS_{android}$ is *Contag Strength Android*, $IB_{android}$ is *Installed Base Android*, PA_{MOS} is *Potential Adopter of MOS* and IB_{Other} is *Installed Base of Other MOS*. The sum in the denominator is a measure of the total addressable market of all MOS at any point in time. *Contag Strength Android* by this model depends on $AR_{android}$ and $IB_{android}$ and hence can be expressed by Equation 2.

$$CS_{android} = f(IB_{android}) * g(AR_{android}) \tag{2}$$

The Market Growth Loop (L5) was operationalized in the form of equation (3).

$$\text{Market Expansion} = \text{Market Growth Fraction} * PA_{MOS} \tag{3}$$

3.2 Calibration of SD diffusion model with Structural breaks

The SD simulation model built developed from Figure 1 had to be calibrated for structure and parameter values. The calibration process has been aided greatly by software features commonly termed as Automatic Calibration (AC). The AC methods typically minimize the sum of errors (between observed and simulated values) of chosen model parameters across all observed data points. We followed the three-stage heuristic suggested by Oliva (2003).

Recognizing that the diffusion of Android handsets is marked by a combination of incremental changes and discrete events, the first step in calibration was to identify the presence of structural breaks in model parameter values. We used the Bai-Perron test with Bayesian Information Criterion (BIC) to do so. Table 3 gives the BIC values for different number of breaks for our Android handset sales data. The lowest BIC value is obtained with 4 breakpoints (at 14, 20, 26 and 34 months).

Table 3: BIC Values for Different Number of Breaks in Sales Growth

No. of Breaks	0	1	2	3	**4**	5
BIC Values	29.0428	28.6121	28.4617	28.0805	**28.022**	28.2671

The timing of these breaks was incorporated into the parameter estimation process for *Contagion Strength* using the functional form given in equation (4).

$$Contagion\ Strength_{\text{Android}} = K_{\text{android},0} * e^{(K_{android,1} * IB_{\text{android}} + K_{\text{android},2} * AR_{\text{android}})} \quad (4)$$

$K_{\text{android},0}$ is a constant. Equations (5) and (6) were written to express $K_{\text{android},1}$, $K_{\text{android},2}$ in way that information on structural breaks could be incorporated.

$$K_{\text{android},1} = K_{\text{android},11} * \text{Pulse}(0,14) + K_{\text{android},12} * \text{Pulse}(14,6) + K_{\text{android},13} * \text{Pulse}(20,6) + K_{\text{android},14} * \text{Pulse}(26,8) + K_{\text{android},15} * \text{Pulse}(34,6) \quad (5)$$

$$K_{\text{android},2} = K_{\text{android},21} * \text{Pulse}(0,14) + K_{\text{android},22} * \text{Pulse}(14,6) + K_{\text{android},23} * \text{Pulse}(20,6) + K_{\text{android},24} * \text{Pulse}(26,8) + K_{\text{android},25} * \text{Pulse}(34,6) \quad (6)$$

We calibrated the model using the optimization feature of Vensim Professional (http://vensim.com/optimization/#vensim8217s-optimizer-provides-fast-calibration-of-models-and-discovery-of-optimal-solutions). Table 4 presents fit statistics for the model-generated behavior with calibrated parameters.

Table 4: Fit Statistics for Model Generated Values

	R Square	MAPE
Android Sales	0.9991	8.92%

The calibration also yielded polarity of $K_{\text{android},1}$, $K_{\text{android},2}$, which determine the polarity of loops L3 and L4 and offer insight into how *Installed Base* and *Android Sales* impacted Android diffusion.

4 Conclusion

In this paper, we have focused on calibration issues in SD models of Android diffusion. This technology evolution is marked by discrete events and incremental changes. Hence there is the possibility of changes in model parameters over the period of analysis. We followed a two-step calibration process. The first step consisted of identifying the breakpoints in a rigorous way using appropriate statistical techniques, keeping in mind the dangers of over-fitting inherent in identifying an excessive number of breakpoints. The second phase consisted of calibrating the causal model where parameter values were allowed to change across the breakpoints. Minimization of the gap between observed sales and simulated adoption rate was used as the objective function. The calibration process could also identify changing causal influences in the model structure itself, albeit in a limited way in that changing link polarities may emerge from the analysis. In summary, our work demonstrates the need to be sensitive to the presence of structural breaks in the calibration of SD models. Technology diffusion is one domain in which this is likely to occur, but there can be other domains where this situation may arise as well.

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