A system dynamics approach to technology interaction: From asymptotic to cyclic behaviour

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A b s t r a c t

This paper is an extension and elaboration of previous research on the simulation of three competing technologies that interact. A modified version of the three-technology system is investigated, and some initial system dynamics results are reported illustrating the progression from asymptotic to cyclic behaviour. Technology is considered in this research as a result of innovation, a rate-dependent process that may include several non-linearities due to interaction with the environment and social context. Using bibliometrics as a research data source is an interesting way to trace technology growth patterns very effectively. In this research, the existence of cyclic behaviour in two real life technologies is illustrated using bibliometrics. In this paper, a technology system consisting of three interacting technologies is treated and modelled in a coupled manner where the interacting dynamics is described by the Lotka–Volterra system of differential equations. The effect of interaction between the technologies and the period of cyclic behaviour is illustrated parametrically. Furthermore, the possible uncertain diffusion as well as interaction effect for two of the technologies is also addressed in this research using a Monte Carlo multivariate simulation technique and a system dynamics approach. The research method is exploratory and case based.

Keywords : Technology system ; Modelling ; System dynamics ; Cyclic behaviour ; Simulation

1. Introduction and research method

1.1. Introduction and background

The focus in this paper is on exploring technology diffusion in competing technologies such as information technology, biomedical technology, energy technology laser technology in manufacturing and others. Along this theme, Heidrich et al. (2011) present and evaluate a process chain to enhance flexible manufacturing of optical components by using laser radiation. They specifically show that it is feasible to ablate and polish fused silica in a time which may be profitable from an industrial application point of view. In essence the technology readiness is illustrated.

Werthen (2011) also focuses on technology competitors in photovoltaic (PV) solar-energy industrial applications. He also addresses the importance of lasers in the manufacture of PV applications. Elements of competing behaviour such as improved manufacturing techniques in the arena related to PV are thus highlighted. Another issue for increased competitiveness in lasers namely quality control is addressed by Franz et al. (2011) when they focus on the alternative use of metrology in discussing the implementation of solid-state lasers to increase the operational speed for materials processing with lasers. Wang and Lan (2007) in their research on market share of Fibre to the x technology in Taiwan focus on analytical technology substitution models in combination with scenario analysis. They also suggest how different technology forecast methods may be combined to improve technology forecasting.

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Some of these competing technologies have been addressed recently in system dynamics (Pretorius and Pretorius, 2010; Pretorius et al., 2012) and bibliometrics (Bae et al., 2007) as well as diffusion modelling (Kim et al., 2006; Pretorius and Winzker, 2010) research. The research presented in this paper is an extension of recent research on simulation of bridging technology dynamics (Pretorius and Pretorius, 2010; Pretorius et al., 2012) and is also based on work presented previously by the authors (Pretorius and Pretorius, 2012; Pretorius et al., 2013). It also illustrates how system dynamics may be used as an alternative to analytical technology substitution models as discussed by, for example, for example Wang and Lan (2007).

The approach that technology can be considered as a body of knowledge as well as the result of an innovation process generally non-linear and time dependent is used extensively in this research. This in essence means that technology can be modelled as the integrated result of a rate-dependent innovation process. This results typically in the diffusion of technologies that can co-exist. Nair and Alsthom (2003) refer to the possibility of co-existence of technologies such as dialysis and transplantation of organs in the medical arena.

This technology diffusion process can be modelled in a number of ways. One way is using the Bass diffusion approach (Bass, 2004) with numerical discretization as illustrated previously in the diffusion of computational fluid dynamics (CFD) technology (Pretorius et al., 2011). The aim in that research was to compare different CFD technologies. In the current research the focus is on the possibility of transition from asymptotic to cyclic behaviour of technologies during and after the technology adoption process.

Another technology modelling approach that has been shown to be effective (Pretorius and Pretorius, 2010; Pretorius et al., 2012), especially in exploratory parametric studies is the system dynamics approach. System dynamics was introduced in the 1960s by Forrester, (1971, 1991) in his pioneering research on modelling socio-technical systems using concepts derived from the theory of feedback control. In socio-technical systems, the focus is on a design process that includes social and organisational issues together with technical factors specifically when analysing and designing organisational systems for the benefit of society. In this approach, the rationale is to include social and technical factors when considering the functionality and use of systems.

When addressing social factors in technology systems and, for example, organisations or equivalent social structures, the issue of resistance to change immediately comes to mind. Resistance to change is a factor that has many implications for organisational sustainability (Potocan and Mulej, 2011; Bauer, 1991; Blin and Munro, 2008). In this context, Potocan and Mulej (2011) point to the existence of culture as, for example, a factor resisting change and competitive forces a factor for change in an organisation. Another case in point is illustrated by Blin and Munro (2008) in their discussion of the effect of virtual learning technology on academic teaching behaviour. In their research, it is illustrated that this type of learning technology at the time had very little impact on the social behaviour of the academics. The implication of this is that the interaction or competition parameter between technologies may have been low at the time for the virtual learning technology.

Failure to adopt a socio-technical holistic approach can increase the risk of a system malfunctioning or not contributing to the aim of the organisation as a system to serve society (Baxter and Sommerville, 2011). It is in this socio-technical system thinking approach that system dynamics may be beneficial to test, for example, the influence of various policy changes on organisational effectiveness.

Wolstenholme (1990) in his research defines system dynamics as “a rigorous method for qualitative description, exploration and analysis of complex systems in terms of their processes, information, organizational boundaries and strategies; which facilitates quantitative simulation modelling and analysis for the design of system structure and control.” This definition also points to the roots of feedback control as well as the ability of system dynamics to address the inherently complex nature of systems that interact. This element of feedback control leading to the possibility of cyclic behaviour of control systems due to the inherent nature of the system is then at the heart of this paper. Here the rather dramatic effect of changing some technology system parameters leading to different technology behaviours will be explored.

This paper also illustrates the inherent effectiveness of system dynamics to elucidate the complex behaviour of interacting technology systems in a manner that is complementary to the analytical technology substitution model approach used, for example, by Wang and Lan (2007). The systems thinking approach is also discussed and evaluated extensively by Jackson (2003) when he addresses system dynamics as a complex system approach as opposed to hard systems thinking considered more of a simple system approach. In this complex systems approach to system dynamics, one of the early most important processes of the approach is the problem definition phase.

Proper problem definition leads to appropriate dynamic hypotheses about the problem that can eventually be translated into a system dynamics model. A clear goal is one of the most important drivers of success of a modelling process. As problem definition adds to the clarity of purpose, it is or should also be one of the most important parts of the system dynamics modelling process. Good dynamic hypotheses generally indicate the dominant factor influencing part of the system behaviour. It is however also important to realize the role of a good hypothesis in indicating that different dominating factors may exist as illustrated by Mashayekhi and Ghili (2010) in their system dynamics approach to modelling the real estate bubble. This may also have a definite effect in technology systems behaviour as illustrated further on in this paper.

Meadows (2008) adds more fundamental methodological insights on the complex behaviour of systems with her thinking in systems approach to system dynamics simulations. Hunger (1995) focuses on the system or holistic perspective in his work and effectively stresses the relationship between soft and hard systems thinking. Elements of the systems thinking approach are used in this paper to shed light on the system dynamics approach used to model the current technology system.

1.2. Research method

The research method used in this paper is qualitative and exploratory in nature and is useful in the early stages of research as indicated by Cooper and Schindler (2006). A systems thinking approach incorporating system dynamics simulations is used in the research to explore the behaviour of a technology system. The technology system considered comprises three interacting technologies. Some of the issues explored in this research relate to the cyclic behaviour of technologies under uncertainty of diffusion as well as technology interaction.

In the first part of the research a system dynamics model of the technology system is conceptualized using in essence a systems thinking approach. Model parameters are chosen to reflect a situation where one technology acts as a bridge between the development phases of two other technologies leading to asymptotic technology behaviour.

The system dynamics model presented is based on previous work by Ahmadian (2008) for deterministic conditions without uncertainty. For this part of the research, a case study method also supported by Leedy (2005) is used to explore the effectiveness of system dynamics as a theoretical modelling basis for simulating the technology interaction. This in essence forms the basis for evaluating the technology system dynamics model and building confidence in the model.

The aim of this research focuses then on evaluating to some extent a technology system dynamics model incorporating three interacting technologies. The focus is on the possibility of transition from asymptotic to cyclic behaviour of the technology system whilst also incorporating the uncertainty of diffusion as well as interaction of a technology or technologies. This is also based on previous research on related topics (Pretorius and Pretorius, 2010, 2012; Pretorius et al., 2012).

A further research objective is to establish the effect that the dynamic model parameters may have on the extent of the cyclic behaviour specifically relating to the period of oscillation of the technology system. In this case, the system dynamic model is modified to some extent to show under what circumstances limit cycle behaviour can be observed and what the effect is of changing some interaction parameters.

This work is also based on some research presented by Mamat et al. (2011) considering a three tier food chain. The modified technology system dynamics model presented in this paper is based on the Lotka–Volterra model encapsulated by Mamat et al. (2011). The effect of model parameters on limit cycle behaviour for this technology system is explored using the system dynamics model.

Part of the research presented here is an extension of the research of Mamat et al. (2011) as well as Chauvet et al. (2002). Both these researchers (Chauvet et al., 2002; Mamat et al., 2011) explain the possibility of existence of periodic solutions of the Lotka–Volterra system of dynamic differential equations. They focus on the existence of a Hopf bifurcation point indicating periodic solutions around this point. The analytical Lotka–Volterra periodic solutions for two competing species are qualitatively shown to be similar to the periodic occurrences of hare and lynx in the Hudson Bay area.

In summary, the system dynamic simulation results are presented in this paper for three sets of case studies. First, the system dynamic model is used with model parameters that represent in some sense the asymptotic behaviour of an interacting technology system showing possible simulated bridging behaviour of one of the technologies. The next set of case studies explored is indicative of the possibility of cyclic behaviour of technologies. In this case, the technology system dynamic parameters are shown to be of a certain characteristic to ensure simulated cyclic behaviour. The third set of case studies represents the effect of uncertainty in some dynamic parameters where cyclic behaviour of technologies can occur.

This research paper also qualitatively compares some system dynamics simulation results for a technology system containing three interacting technologies with the results shown by Schmoch (2007). Schmoch (2007) provides some evidence of cyclic technology behaviour using bibliometrics (Bae et al., 2007) and patent analysis. He shows that industrial robot technology went through a double boom cycle across a period of approximately 15 years. He also mentions that laser technology in manufacturing shows signs of a double boom cycle by analyzing patent data. He however does not provide any technical bibliometrics data for the laser technology in manufacturing.

Some new bibliometrics data for the laser technology is also gathered and analysed in this paper to compare qualitatively with the results of some system dynamic simulations. Both these technology case studies' bibliometrics results are used to increase confidence in the usefulness of the technology system dynamics model.

The next sections in this paper introduce firstly the basic development of the three-technology system dynamics model. Thereafter, some system dynamic simulation results are presented for the technology case set with bridging behaviour. Then the simulation results gathered for the case study set with cyclic technology behaviour are discussed. In the last section, the simulation results for cyclic technology behaviour with parameter uncertainty are presented and discussed.

2. A technology system dynamics model

In this research paper, the technology system dynamics model developed and shown in Fig. 1 relates to the non-linear system of differential equations similar to that used by Ahmadian (2008). The competing technologies are denoted by X, Y and Z, respectively. In this first version of the Lotka–Volterra system of differential equations, all the parameters used have non-zero values associated with them. In these equations, A_i denote the growth rate or logistic parameter for technology i when it is living alone; this is also referred to in this paper as the diffusion coefficient that can be related to technology marketing effort; B_i is the limitation parameter for species i related to niche market capacity; and C_i as well as D_i are the interaction coefficients. In this paper, these coefficients C_i and D_i are also sometimes equivalently referred to as competition parameters denoting the effect of competition between technologies:

$$\begin{aligned}
\frac{DX}{dt} &= A1*X - B1*X^2 - C1*X*Y - D1*X*Z \\
\frac{DY}{dt} &= A2*Y - B2*Y^2 + C2*Y*Z - D2*X*Y \\
\frac{DZ}{dt} &= A3*Z - B3*Z^2 + C3*Z*X - D3*Z*Y
\end{aligned} \tag{1}$$

In this first model, Technology Z can be considered to be a bridging technology under certain parameter conditions. The parameter values used and shown in Table 1 relate to this mode of a bridging technology considered in case study set number one. The parameter values used in Table 1 are similar

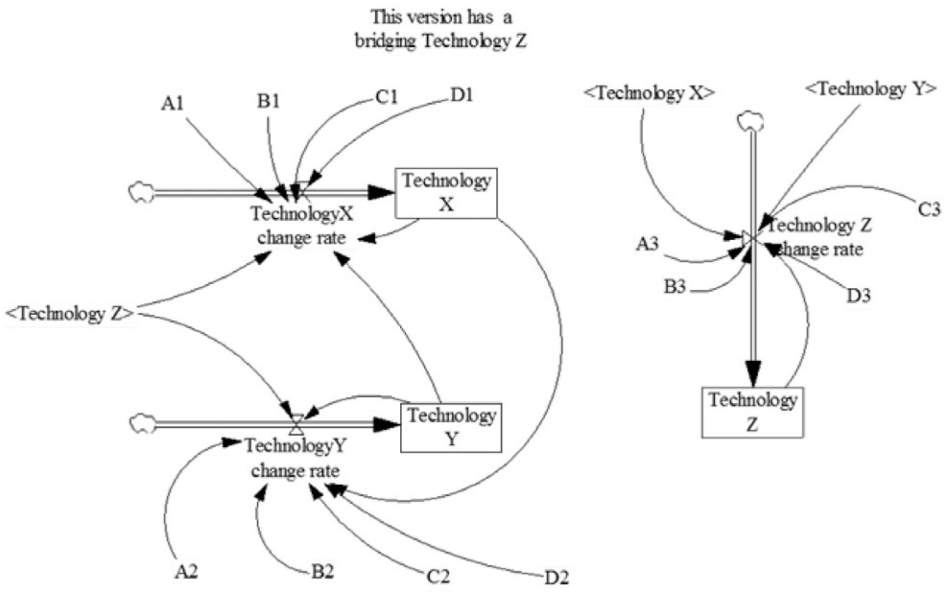

Fig. 1. The technology system dynamics model.

to those used by Ahmadian (2008) in his deterministic system dynamics simulations. This is done to be able to evaluate the current system dynamics model referred to in Fig. 1 against some previously published data.

To illustrate the effect of system parameter values and to explore the possibility of transition to cyclic behaviour of technology, the following modified system of non-linear differential equations describing an alternative competing technology system represents the major research focus in this paper. This relates to the technology case study set number two referred to in Section 1.2. Here some system parameter values (B1, D1, B2, B3 and C3) are considered to be zero. All further parameter values shown are considered to be positive. The parameter values used to do model computer simulations in Vensim Software (2012) are shown in Table 2:

$$\begin{aligned}\frac{DX}{dt} &= A1 * X - C1 * X * Y\\ \frac{DY}{dt} &= -A2 * Y - C2 * Y * Z + D2 * X * Y\\ \frac{DZ}{dt} &= -A3 * Z + D3 * Z * Y\end{aligned} \qquad (2)$$

The parameter values used in this simulation are chosen to be similar to the ones used by Mamat et al. (2011) to be able to compare the current system dynamic simulation results to some previously published values for deterministic conditions. The parameter values are furthermore chosen to illustrate the possibility of cyclic behaviour of interacting technologies. Both Mamat et al. (2011) and Chauvet et al. (2002) in their analytic solutions indicate the possibility of sustained periodic solutions for the combination of parameters associated with equation set (2):

$$A3 = A1 * \frac{D3}{C1} \qquad (3)$$

Eq. (3) indicates the Hopf bifurcation point for Eq. (2), and if D3 is chosen as 0.5, A3 is calculated as 0.5 from Table 2.

The technology system modelled using Eq. (2) pertinently differs from the technology system using Eq. (1) in the sense that parameters A2, A3, C2, D2 and D3 have opposing signs in Eq. (2). From a systems thinking perspective (Jackson, 2003), this reflects the dynamic hypothesis that for this case the innovation of Technology X or equivalently the Technology X change rate is positively influenced by the existence of Technology X through A1 and negatively influenced by the existence of competing Technology Y through the interaction coefficient C1.

In the same systems thinking approach, it is hypothesised that the innovation of Technology Y or equivalently the Technology Y change rate is negatively influenced by the existence of Technology Y through the obsolescence rate A2 of Technology Y, while it is positively influenced by learning experiences gained from interaction with Technology X through interaction coefficient D2. At the same time, Technology Y change rate is negatively influenced by its interaction with

Table 1
Some typical model parameters for Eq. (1) related to case study set number one.

	Model parameters, Eq. (1)											
	A1	B1	C1	D1	A2	B2	C2	D2	A3	B3	C3	D3
Certain	0.1	0.01	0.1	0.1	0.1	0.01	0.1	0.1	0.1	0.01	0.1	0.1
Uncertain	C3 = RANDOM NORMAL(0.01,0.3.0.1,0.05)											

Table 2
Some typical model parameters for Eq. (2) related to case study set number two and three.

	Model parameters, Eq. (2)											
	A1	B1	C1	D1	A2	B2	C2	D2	A3	B3	C3	D3
Certain	0.5	0	0.5	0	0.5	0	0.5	0.5	0.5	0	0	0.5 or 0.45
Uncertain	A1 = RANDOM NORMAL(0.3,0.8.0.5,0.05), D3 = RANDOM NORMAL(0.3,0.8.0.5,0.05)											

Technology Z that is preying on Y through the interaction coefficient C2.

This realisation of dynamic hypotheses also shows how a difference in fundamental mechanisms (see the change from Eqs. (1) and (2) illustrating the above-mentioned hypotheses) may be achieved as indicated, for instance, by Mashayekhi and Ghili (2010). The above-mentioned discussion then also serves as motivation why the parameter set shown in Table 2 was used for Eq. (2) resulting in the zero choices for parameters such as, for example, B1, D1 and C3.

The discussion on parameters leading to dynamic hypotheses for the technology system in this paper as presented above can also be related to the matter of decisions and policies in technology development. For instance, the relationship indicated for innovation of Technology X in Eq. (2) can be seen as the result of a decision and policy during technology development to stimulate growth of Technology X through marketing effort related to coefficient A1 and while at the same time taking care of a decline in Technology X through competition of Technology Y using the competition coefficient C1 as decision instrument. This deductive reasoning from a decision and policy point of view then also substantiates in some sense the adapted choice of parameters for Eq. (2) as indicated in Table 2.

Currently, there are a number of computer simulation tools available to simulate system dynamics models such as the one of the competing and interacting three-technology system indicated in Fig. 1. The one used in this research is Vensim DSS (Vensim Software, 2012). In the Vensim system dynamics model, the boxes denote level variables (for example the emerging Technology Y in this case).

The level variables are generally the result of numerical integration of rate variables such as, for example, Technology Y change rate associated with the innovation of Technology Y denoted in Fig. 1 as a valve symbol. In this context, the rate variables can be considered as the innovation rate of the relevant technology. The arrows indicate the respective relationships between the variables indicated in, for example, Eq. (1). The technology system shown in Fig. 1 with more than 20 relationships indicated by arrows can thus be considered to be a complex or complicated system with multiple interactions.

3. Some results for bridging interaction: case set number one

The following system dynamic simulation results using Eq. (1) and the model depicted in Fig. 1 for case study set number one have been obtained using Vensim. All the system dynamics results shown have been obtained using numerical integration and a fourth order Runge Kutta method combined with time intervals of 0.01 year. All results in the graphs are shown in dimensionless form for technology levels and technology change rates. For this case study set, the dimensionless technology levels have been chosen between zero (0) and around ten (10) with zero to one representing low technology levels and eight to ten high levels.

The parameter values used in these simulations and indicated in Table 1 have been chosen to be similar to those used by Ahmadian (2008) for comparison purposes and to indicate that a technology system under this specific set of conditions pertaining to the decisions and policies related to the parameter values is able to generate asymptotic behaviour for the technology levels. The initial dimensionless technology levels used in the system dynamics simulations were 5 (indicating a medium initial technology level), 0.01 and 0.01 for Technology X, Y and Z, respectively.

The dimensionless system dynamic simulation responses shown in Fig. 2 for deterministic parameters indicate quite clearly the bridging effect of Technology Z from year 6 to year 24 where Technology Y still shows very low responses while the defending mature Technology X has already started its demise. The bridging Technology Z reaches a peak in dimensionless activity level just below 8 at approximately year 17.

These results are similar to those obtained by Ahmadian (2008) for deterministic conditions and thus reinforces confidence in the current technology system dynamics model developed in Vensim. These results shown in Fig. 2 are indicative of the asymptotic behaviour of this particular technology system with parameters as indicated in Table 1. Further similarity of these system dynamics results when compared with analytical results obtained by Wang and Lan, 2007 for technology forecasting of Internet access technologies strengthens the confidence in ability of the current system dynamics model to capture the essential bridging and competing characteristics of this technology system.

The results with uncertainty in bridging technology interaction for essentially asymptotic behaviour are not included and discussed in this paper but can in principle be referenced in (Pretorius et al., 2012). The aim of this paper was more focussed on the effect of a change in system parameters related to a change in dynamic hypotheses reflecting a shift in dominant behaviour mechanism that could lead to and reflect a possible change from asymptotic to cyclic behaviour of the technology system. These results for cyclic behaviour are included and discussed in more detail in the next section.

4. Some results with cyclic behaviour: case sets two and three

All results in the graphs for case sets two and three are again shown in dimensionless form for technology levels and technology change rates. For these case study sets, the dimensionless technology scale levels have been chosen between zero (0) and five (five) with zero to one representing low technology levels and four to five high levels. The choice of level five as high was again to be able to compare these simulation results with some of those presented by Mamat

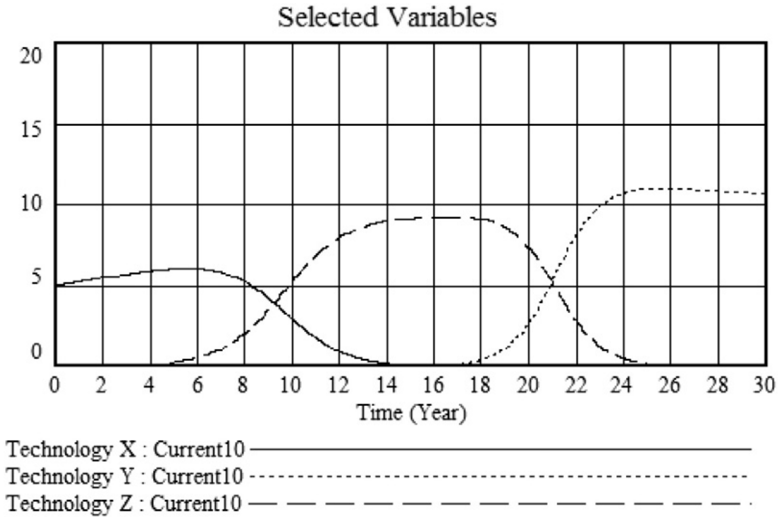

Fig. 2. Technology X, Y and Z simulated transient response indicating bridging effect of Technology Z.

et al. (2011). The dimensionless scale from zero to five for these results can also be transformed if necessary from zero to ten if required.

4.1. Some results with deterministic parameters: case set number two

This section aims to explore the effect that a somewhat drastic change in technology system dynamic model parameters essentially reflecting a change in dynamic hypotheses can have on the technology response. The following system dynamic simulation results using Eq. (2) and the model in Fig. 1 have been obtained using Vensim.

The parameter values used in the computer simulations and indicated in Table 2 have been chosen to be similar to those used by Mamat et al. (2011) for comparison and evaluation purposes and to indicate that a technology system under this specific set of conditions pertaining to the decisions and policies related to the parameter values is able to generate cyclic behaviour for the technology levels. These parameter values differ somewhat drastically from those on Table 1 used for simulations presented in the previous section. Notable are some zero and effectively negative parameter values in Table 2 compared to Table 1. The reasons for these specific parameter choices have been motivated in a previous section.

The initial technology levels used in the system dynamics simulations were low dimensionless levels 0.5, 0.5 and 0.5 for Technology X, Y and Z, respectively. Monte Carlo multivariate simulations with 200 iterations were done in the cases where uncertainty was modelled.

Two initial parametric situations of interaction were considered for Technology Z where parameter D3 was chosen as 0.5 and 0.45, respectively, to illustrate the possibility of limit cycle behaviour for three technologies similar to the cyclic behaviour illustrated by Mamat et al. (2011) for food chain behaviour. Pertaining to the interacting technology system, Figs. 3 and 4 show simulation results for parameter D3 = 0.45, and Fig. 5 indicates the effect of change in parameter D3 from 0.5 to 0.45.

Another situation was considered where the diffusion parameter A1 associated with Technology X was changed parametrically from 0.5 to 0.1 to explore the effect this may have on the period of oscillation in the technology system. Fig. 6 indicates the effect of this change on Technology X performance.

If one compares the results of Figs. 2 and 3 the qualitative difference in technology response should be evident. Technology X in Fig. 2 shows an asymptotic behaviour to zero with no oscillations. In Fig. 3, Technology X shows an oscillatory cyclic behaviour. Furthermore, the bridging role of Technology Z seems to have fallen away giving rise to cyclic behaviour for Technology Z as well.

In Fig. 3, the maximum levels of technology activity for Technology X occurs at year 5.6 with value 2.822 and at year 17.3 with value 2.678. This indicates a simulated period of oscillation of approximately 11.7 years for Technology X. For Technology Y, the maxima occur at year 7.4 with a value of 2.643 and at year 19.21 with a value of 2.575. This reflects a period of oscillation of approximately 11.8 years for Technology Y.

The non-linearity embedded in the current systems dynamics model is evident from the transient simulation responses for Technology X, Y and Z change rates depicted in Fig. 4. The response for Technology X change rate is not sinusoidal as for the typical linear differential equations. The difference in maximum negative and positive change rates is also evident. At year 6.8, the minimum value is −1.274 and at year 15.91 the maximum value is 0.6346.

These simulation results are important from a technology management perspective. The difference in duration of simulated negative and positive Technology X change rates may also have important technology management implications in the sense of, for example, different expenditures for the different phases of the technology cycle. For Technology X, the duration of negative change rates is 4.46 years, from year 5.57 to year 10.03. The duration of positive change rates for Technology X is 7.26 years, from year 10.03 to year 17.29. This simulated technology performance may thus, for example, be used in planning for the cost of technology development in different

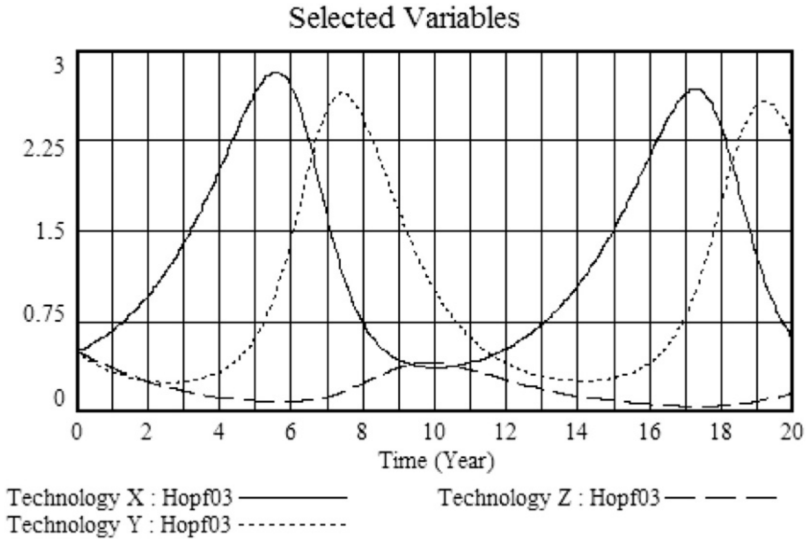

Fig. 3. Technology X, Y and Z simulated transient response indicating co-existence and cyclic behaviour; D3 = 0.45.

phases of a technology system that tends to exhibit oscillating behaviour.

For the case where D3 is chosen as 0.5, a Hopf bifurcation point for parameter A3 is calculated as 0.5. For this set of parameter values, sustained limit cycle periodic behaviour for all three technologies is simulated as shown for Technology Z in Fig. 5. In Fig. 5, Technology Z has a periodic response with constant amplitude for D3 = 0.5 and A3 = 0.5 at the Hopf bifurcation point.

If D3 is changed to 0.45, the response of Technology Z changes to a periodic response with decreasing amplitude as shown in Fig. 5. For the case of D3 = 0.5, the minimum value of Technology Z occurs at year 5.56 with a value of 0.0878 and at year 16.56 with a value of 0.0879. This implies a period of oscillation of 11.0 years for Technology Z. This is effectively the same period of oscillation for Technology X and Technology Y simulated as 11.03 years. These values concur with values indicated by Mamat et al. (2011) in their research for this parameter values. This further establishes confidence in the current system dynamic model for three interacting technologies.

From Fig. 6, it should be evident that a change from 0.5 to 0.1 for diffusion parameter A1 associated with Technology X has dramatic effect on the period of oscillation of Technology X. At year 2.11, the first minimum level of 0.4420 and at year 33.39 the next minimum level for Technology X occurs. This implies a period of oscillation of approximately 31.3 years, which is nearly three times the value of 11.7 years quoted before for the case of diffusion parameter A1 = 0.5.

This may have serious technology management consequences to sustain technology profitability over such a prolonged period of more than 30 years. This lower value of

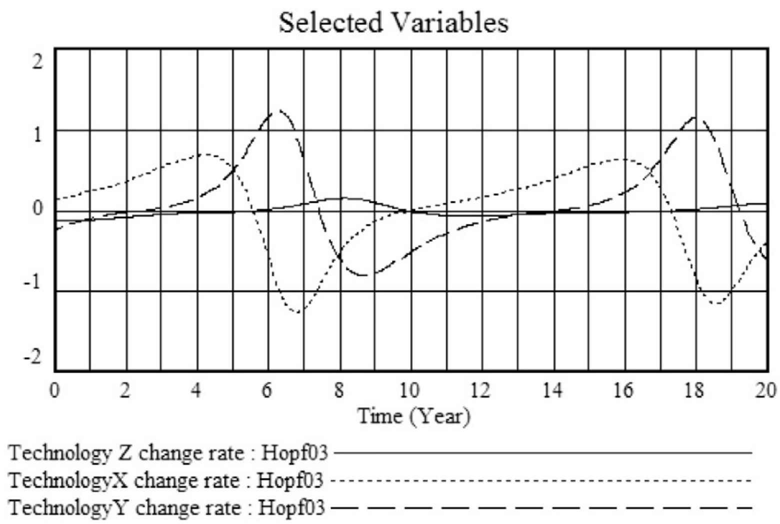

Fig. 4. Technology X, Y and Z change rates simulated transient response indicating non-linear innovation; D3 = 0.45.

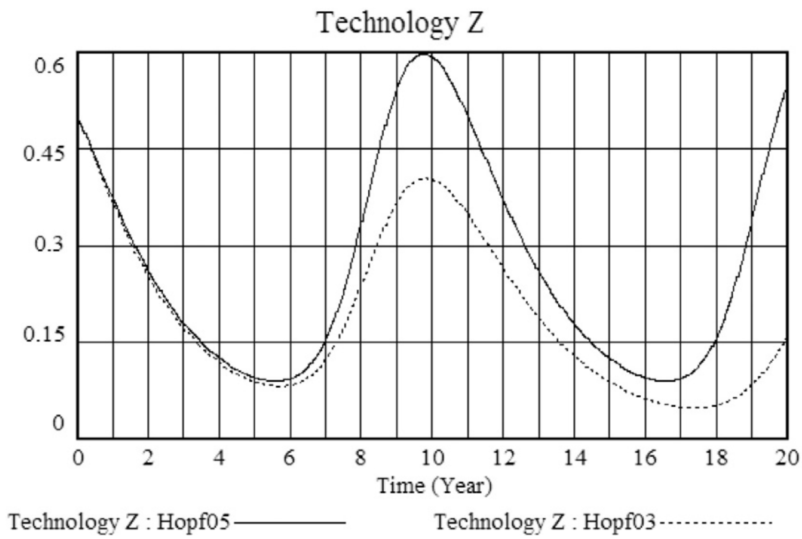

Fig. 5. Technology Z simulated transient response indicating effect of interaction parameter D3; D3 = 0.45 and D3 = 0.5.

A1 = 0.1 is then perhaps indicative of a relatively low key technology marketing initiative that may need to be intensified to sustain profitability. This parametric study on the influence of diffusion parameter A1 is then indicative of the usefulness of the technology system dynamics model in warning against the possible negative effects of too little attention on technology marketing. This is related to the prolonged cyclic behaviour period of Technology X with decreased values of diffusion parameters. The usefulness of the simulation results from a technology management point of view is thus illustrated again.

It can also be seen in Fig. 6 that a change of diffusion parameter A1 in the opposite direction from 0.5 to 0.6 has the effect of decreasing the period of oscillation of Technology X from 11.7 years to 9.6 years in the first technology cycle.

4.2. Some results with uncertainty: case set number three

To further explore the effect of model parameters in this technology system dynamics model for Eq. (2), the effect of uncertainty in diffusion parameter A1 as well as in the competition parameter D3 is considered. As indicated in Table 2, the effect of uncertainty in the interacting technology system is modelled here by introducing a random normal distribution on parameters A1 and D3 with a mean value of 0.5 and a standard deviation of 0.05. Multivariate Monte Carlo simulations using 200 iterations for illustration and technology trend purposes were also done in Vensim with the technology system dynamics model shown in Fig. 1 (Eq. (2)).

When interpreting the results shown in this section, it is important to realise that the Monte Carlo simulation technique

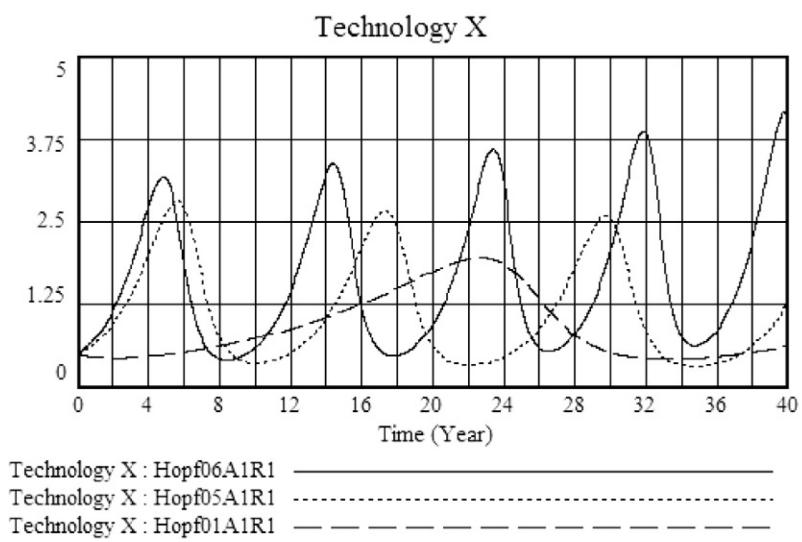

Fig. 6. Technology X simulated transient response indicating effect of diffusion parameter A1; A1 = 0.1, A1 = 0.5 and A1 = 0.6.

employed uses random numbers in the process. Random noise is also generated using a seed number in the computer simulations. Repeated simulations using different seed numbers may produce slightly different results, but the trends are the same and this is what is important in this paper from a technology trend point of view.

Three further cases of uncertainty simulations were considered using the technology system exhibiting cyclic behaviour. First, uncertainty was introduced only in the diffusion or marketing parameter A1 (case 1). Thereafter, uncertainty was introduced in the interaction (competition) parameter D3 separately (case 2). Finally, a combination of uncertainty of D3 and A1 was considered (case 3).

Case 1 resulted in the simulated sensitivity traces for Technology X and Technology Z under uncertainty of diffusion parameter A1 as shown in Figs. 7 and 8. It is notable that the cyclic behaviour is maintained for the range of uncertainty considered. There seems to be a tendency for some of the outlier 95%–100% ranges of simulated traces for both Technology X and Technology Z to diverge with time (increasing ranges of oscillation amplitudes as indicated, for example, in Fig. 8)

At time 7 years from Fig. 7, it can be deduced that under uncertainty of diffusion there is a 25% probability that Technology X level activity will be less than 1.1 and a 25% probability that the activity level will be more than 2.

Fig. 9 shows the simulated sensitivity histogram for diffusion parameter A1 in case 1. It is noted that the simulated response seems symmetrical with a mean of approximately 0.5. This is in line with the specified normal distribution for parameter A1. Furthermore, the simulated sensitivity histogram for Technology X activity levels at year 20 shown in Fig. 10 represents a skew distribution with maximum of 0.5 to 1.

Of importance to note here from a technology management perspective is that uncertainty associated with one part of the technology system (parameter A1 and Technology X in this case) results in uncertain responses in other parts of the system (Technology Z) as well. This can be related to the concept of holism in systems.

From Fig. 11, the cumulative distribution for Technology X at time 20 it can be inferred that there is a probability of approximately of 35% that the Technology X level will be less than 0.25. This information may be useful in technology risk management if compared to the mean value of approximately 1.11 for Technology X at time 20.

Case 2 resulted in the simulated sensitivity traces for Technology X, Technology Y and Technology Z under uncertainty of interaction parameter D3 as shown in Figs. 12 to 14, respectively. What should again be evident on comparison of Figs. 12 to 14 is that an uncertainty in one area (parameter D3 associated with Technology Z) has a rather pronounced effect in other areas, for instance, Technology Y in Fig. 13 where at year 10 the uncertainty range is typically from 0.5 to 1.2 due to interaction effects with Technology Z. At year 10 for this case, Technology Z as shown in Fig. 14 displays an uncertainty range of typically 0.15 to 1.20. This reinforces the concept of holism in technology management: what happens in one part of a system tends to affect the entire system.

Case 3 resulted in the simulated sensitivity traces for Technology X, Technology Y, Technology Z under uncertainty of combination of interaction parameter D3 and diffusion parameter as shown in Figs. 15–17, respectively. Careful inspection of Fig. 16 illustrates effectively the rather pronounced effect of combination of uncertainty of diffusion (A1) and interaction (D3) on Technology Y uncertainty with values ranging typically from 0.2 to 1.9 at year 10.

Figs. 18–20 show the simulated sensitivity histograms at year 10 for interaction coefficient D3 (case 2) compared to combination of interaction coefficient D3 and diffusion parameter A1 (case 3). What is notable in, for example, Figs. 19 and 20 should be the change in appearance of histograms for Technology Y and Technology Z in the case of combination of uncertainty of parameters.

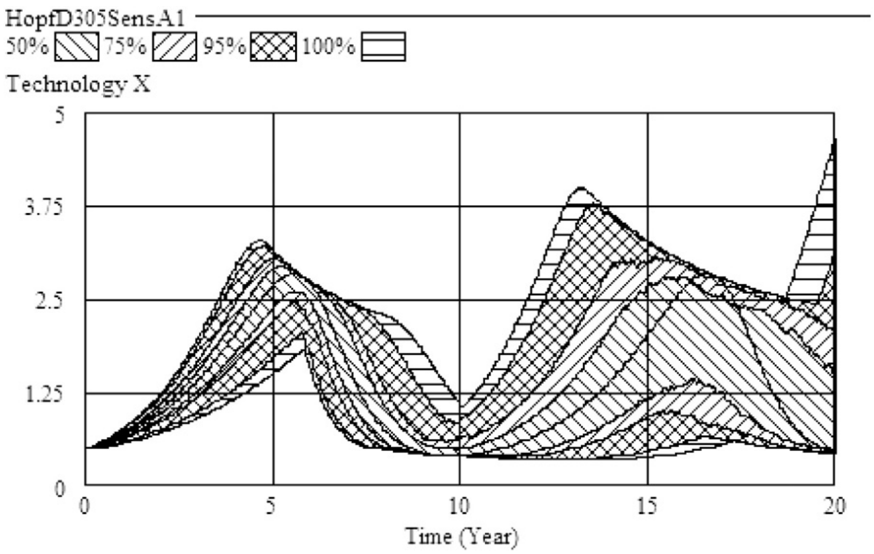

Fig. 7. Technology X sensitivity trace ranges under uncertainty of diffusion parameter A1 (case 1).

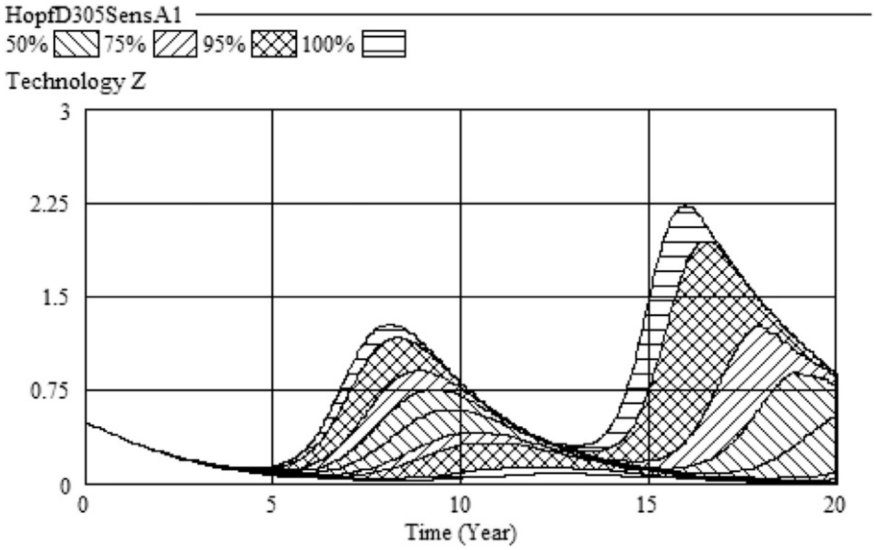

Fig. 8. Technology Z sensitivity trace ranges under uncertainty of diffusion parameter A1 (case 1).

Also evident should be the general increase in standard deviation represented in the spread of technology levels around the mean for the case of combination of uncertainty. See, for example, the increase in standard deviation from 0.075 to 0.148 inferred from Fig. 20 and Table 3 for Technology X.

From Fig. 21, the cumulative distribution for Technology Y at time 10, it can be inferred that there is a probability of approximately 20% that the Technology Y level will be less than 0.4 for the case of combined uncertainty (D3A1) considered here. This information may again be useful in technology risk management if compared to the mean value of approximately 0.96 for Technology Y at time 10

A general observation that may be made from the simulated technology system statistics presented in Table 3 is that the norm value representing the standard deviation divided by the mean increases when combined uncertainty of parameter D3 and A1 is considered. Compare, for example, the increase in norm value from 0.174 to 0.3 at year 10 for Technology X when uncertainty of D3 is combined with uncertainty in A1. This calculated norm value then represents a way possible way of characterising and comparing risk levels in technology systems.

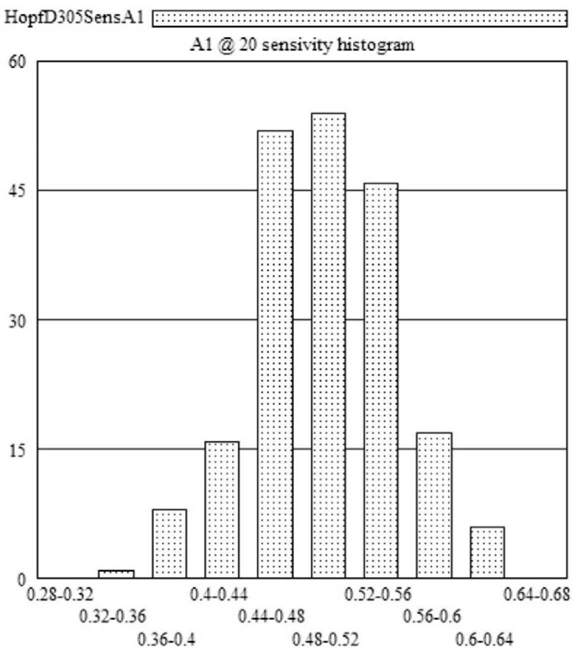

Fig. 9. Typical sensitivity histogram for diffusion parameter (A1) at year 20 (case 1).

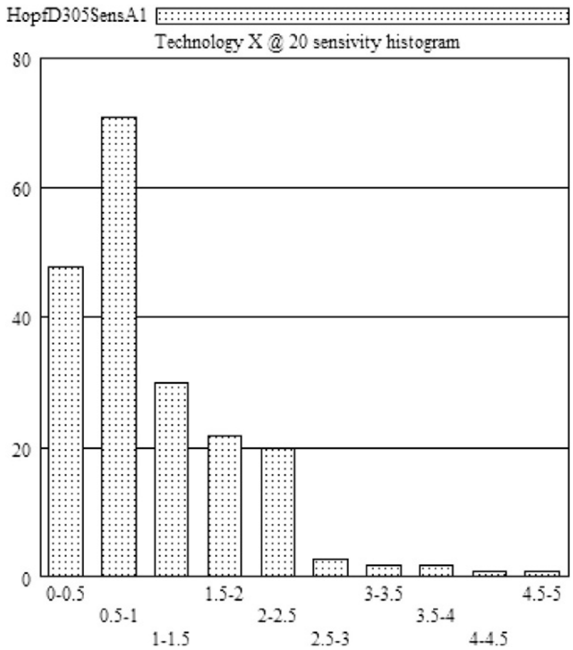

Fig. 10. Typical sensitivity histogram for Technology X under diffusion uncertainty (A1) at year 20 (case 1).

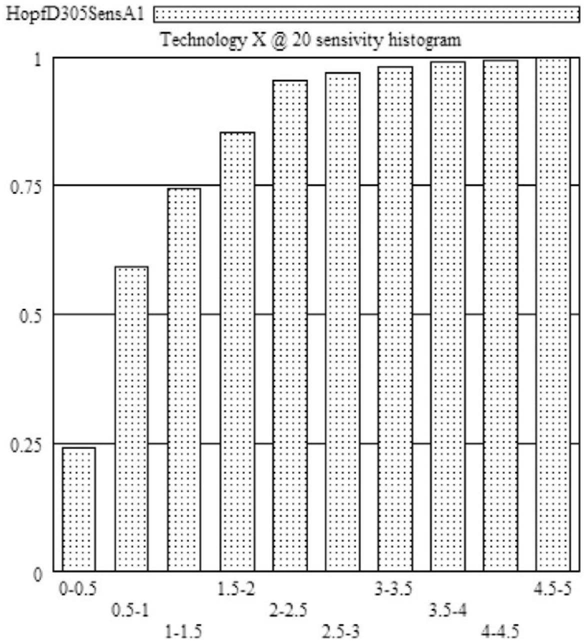

Fig. 11. Typical sensitivity cumulative distribution function for Technology X under diffusion uncertainty (A1) at year 20 (case 1).

5. Basic evaluation of simulation results with cyclic behaviour

To evaluate the simulation results obtained for the three-technology system in the previous sections, an attempt was made to find real case technology data that reflects some oscillatory behaviour. The work of Schmoch (2007) for industrial robot technology and some further data collected for the technology of lasers in manufacturing are considered for comparison purposes with the current simulation results.

For the case of industrial robot technology, Schmoch (2007) describes the existence of cyclic behaviour of the technology. He uses bibliometric analysis (Bae et al., 2007) in the form of patent and publications analysis over a 33-year period from 1970 to 2002 and illustrates the existence of a double boom cycle over a 15-year period as shown in Fig. 22. The data shown in Fig. 22 have been normalized to year 32 data (210 for patents and 968 for publications).

He specifically states that the scientific trends for industrial robot technology as described by publication indices precede the technological trends by several years. These technological activity trends for industrial robot are shown in Fig. 22, where the phase difference between patent and publication cyclic behaviour can be seen from approximately year 10 onwards.

On comparison of Figs. 3 and 22, it is evident that both the simulated and real case data show evidence of cyclic behaviour for the technologies considered. The simulated period of oscillation for Technology X (11.7 years) is also in the same range as that for the industrial robot technology data (approximately 15 years).

This also supports the confidence in the system dynamics model for the case of cyclic behaviour of the technology. A word of caution is necessary; this is a case study simulation only. Schmoch (2007) also warns that not all technologies exhibit cyclic behaviour. For this case, however, qualitative similarity of simulated technology responses and real case data for industrial technology has been successfully demonstrated.

Schmoch (2007) also refers to the case of double boom cyclic behaviour of laser technology in manufacturing. He however does not provide detailed data to support his statement. Some additional bibliometrics case study research data was captured concerning the laser technology in manufacturing for the period 1970 to 2000 in this current research. Two data bases were used: Google Scholar as well as Engineering Compendex. The Compendex bibliometrics data was also gathered as the Google Scholar data pointed to some possible cyclic behaviour but this bibliometrics data did not present as clear a picture of this behaviour. These technology

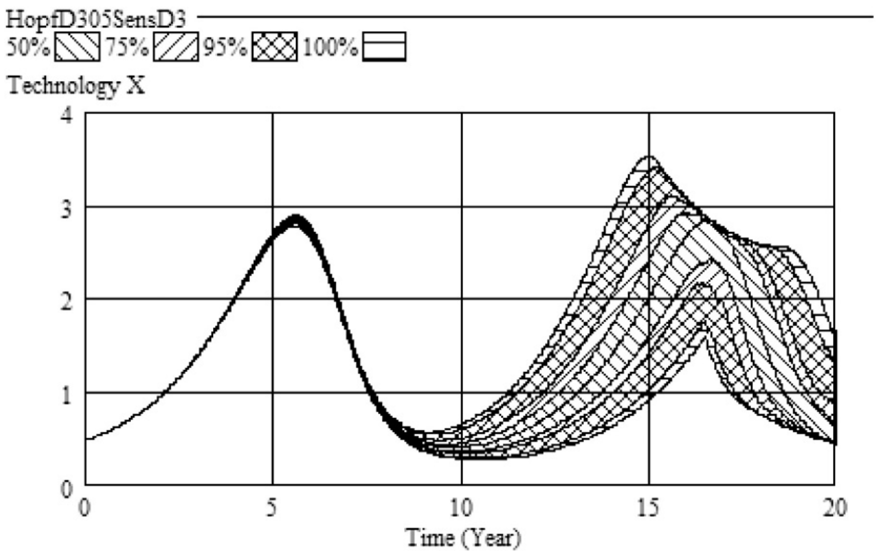

Fig. 12. Technology X sensitivity trace ranges under uncertainty of interaction coefficient D3 (case 2).

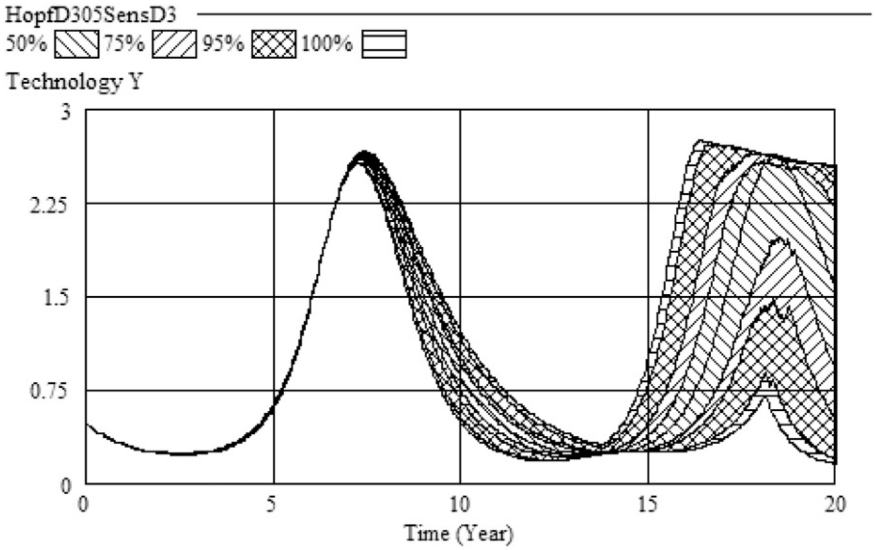

Fig. 13. Technology Y sensitivity trace ranges under uncertainty of interaction coefficient D3 (case 2).

cyclic behaviour patterns displaying evidence of a double boom cycle are shown in Figs. 23 and 24. The data shown in these figures have been normalized to year 18 data From this an approximate technology cycle period of 7 years should be evident for the technology of lasers in manufacturing across the time range considered.

6. Conclusion

A technology system dynamics model considering three interacting technologies has been introduced using elements of the systems thinking approach also supported by Jackson (2003) and Meadows (2008). Three case sets of general application of the system dynamics model focussing on the transition from asymptotic to cyclic behaviour of the technology system have been considered. These three system dynamics modelling instances are also considered useful for managers in the practical management of technology as they provide a basis for making decisions between, for example, a set of policies focussed on a combination of marketing and competition leading to asymptotic behaviour of technologies as opposed to a set of policies based on a reduced combination of marketing and competition factors. The third set of modelling instances introduced has been based on the premise that policies may have an element of uncertainty associated with them. These simulation results are again of practical usefulness for technology managers in assessing, for instance, some of the risks associated with technologies.

In the first instance as part of case set one, it has been illustrated how a bridging technology (Z) effect can be

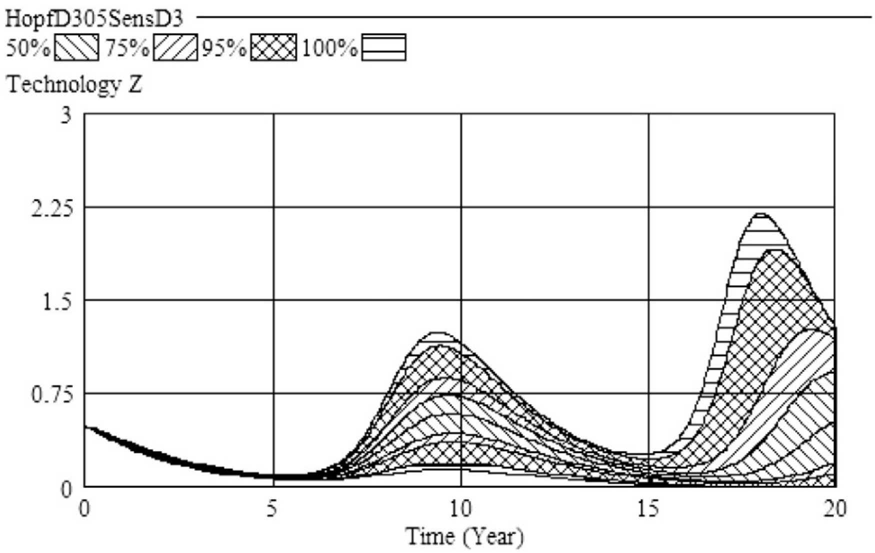

Fig. 14. Technology Z sensitivity trace ranges under uncertainty of interaction coefficient D3 (case 2).

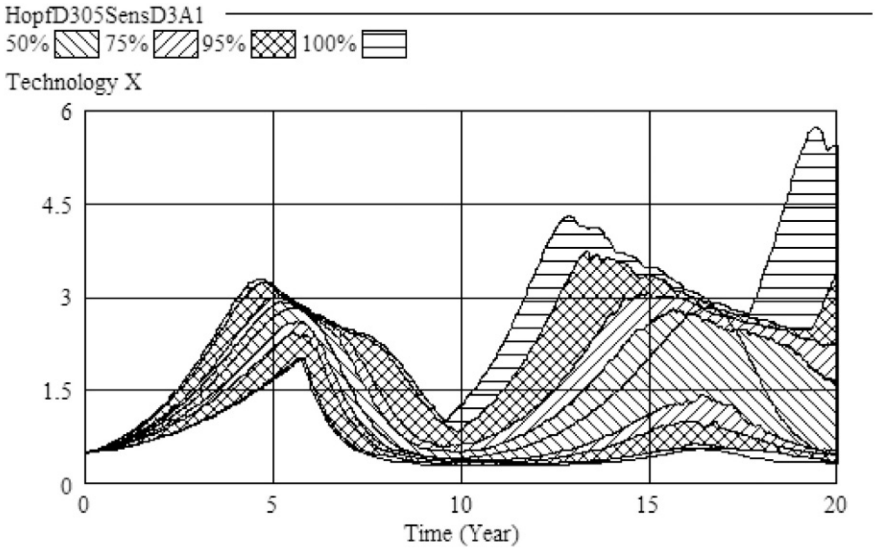

Fig. 15. Technology X sensitivity trace ranges under combined uncertainty of interaction coefficient D3 and A1 (case 3).

constructed by appropriate choice of positive system dynamics model deterministic parameters mainly associated with an appropriate balance of marketing and competition policies. The simulated system dynamics results for this case concur with previously published results (Ahmadian, 2008; Pretorius et al., 2012) showing asymptotic transient behaviour of the technologies. This provides some confidence in the technology system dynamics model.

The second simulation instance as case set two has attempted to show the rather drastic effect that choice of system parameters can have on the simulated behaviour of the technology system dynamics model. For this instance, some parameters have been chosen as zero and negative similar to the work of Mamat et al. (2011) on food chain behaviour. This resulted in a change of asymptotic to cyclic transient behaviour for all three technologies (X, Y and Z) indicated by simulation results. This is essentially similar to the results reported by Mamat et al. (2011) again resulting in more model confidence.

The effect of change in diffusion coefficient on the cyclic performance of the technology system has been parametrically shown in simulations. It has been shown that a smaller diffusion coefficient A1 associated with Technology X in the technology system dynamics model results nominally in extended periods of oscillation of up to 3 times the original period. This influence of diffusion parameter A1 can be considered as an indication of the practical usefulness of the technology system dynamics model to technology managers in warning against the possible negative effects of a policy based on too little attention on technology marketing. One of the practical advantages of the system dynamics method employed

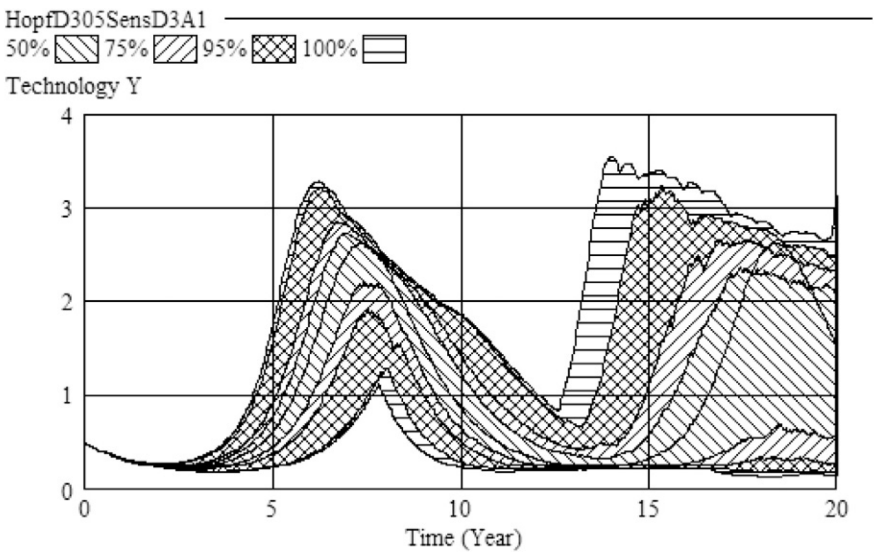

Fig. 16. Technology Y sensitivity trace ranges under combined uncertainty of interaction coefficient D3 and A1 (case 3).

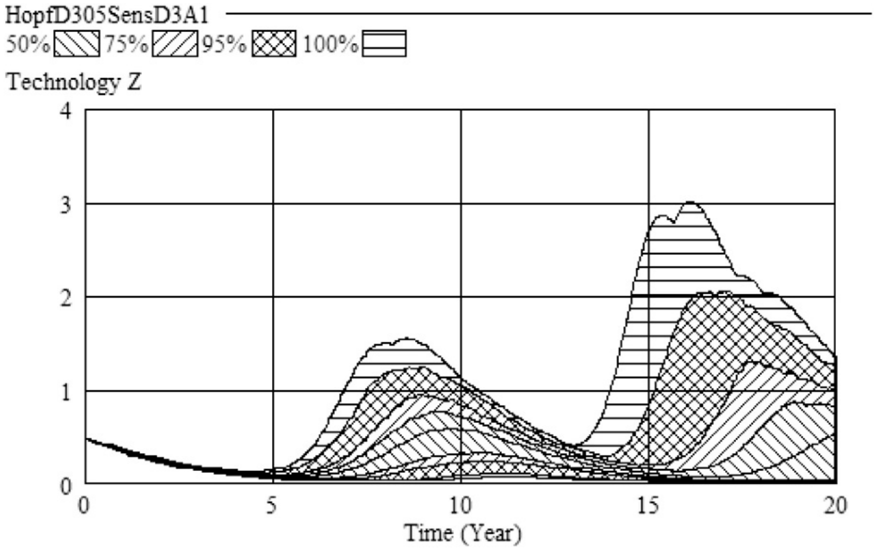

Fig. 17. Technology Z sensitivity trace ranges under combined uncertainty of interaction coefficient D3 and A1 (case 3).

in this research for technology managers is the relative ease with which parametric comparisons could be done on, for instance, the effect of this change in the diffusion coefficient.

Uncertainty of diffusion for the first technology (X) as well as uncertainty of interaction for the third technology (Z) has also been modelled as part of case set three comprising three subcases denoted case 1, case 2 and case 3. A Monte Carlo approach has been used in the system dynamics model considering three cases of parameter uncertainty. These simulation results mainly focus on the effect that uncertainty has in the introduction of technology management policies associated with, for instance marketing and competition of technologies. In simulation case 1, only the effect of diffusion uncertainty in parameter A1 was considered. Case 2 considered only the effect of uncertainty of interaction parameter D3, whereas case 3 introduced the combination of uncertainty of diffusion and interaction simultaneously. Simulation results pertaining to case 1 for two technologies (X and Z) with uncertainty in diffusion show nominally cyclic transient behaviour for all uncertainty ranges considered. Although the

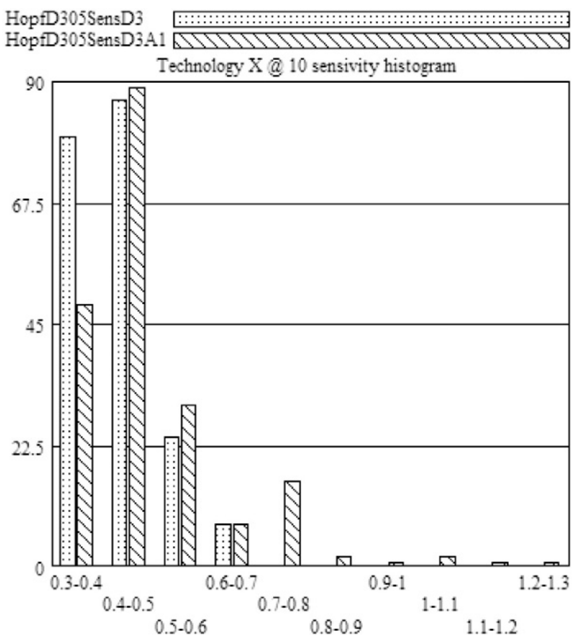

Fig. 18. Typical sensitivity histogram for Technology X under combined uncertainty of diffusion coefficient A1 and interaction coefficient D3 at year 10 compared to uncertainty of interaction coefficient D3 only (cases 2 and 3).

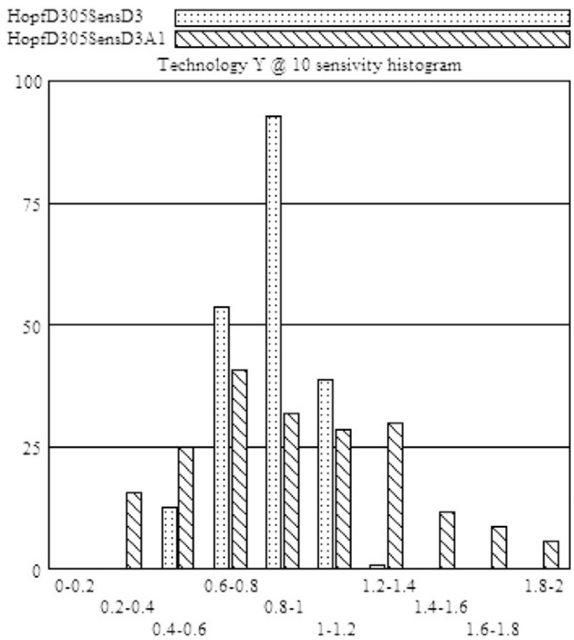

Fig. 19. Typical sensitivity histogram for Technology Y under combined uncertainty of diffusion coefficient A1 and interaction coefficient D3 at year 10 compared to uncertainty of interaction coefficient D3 only (cases 2 and 3).

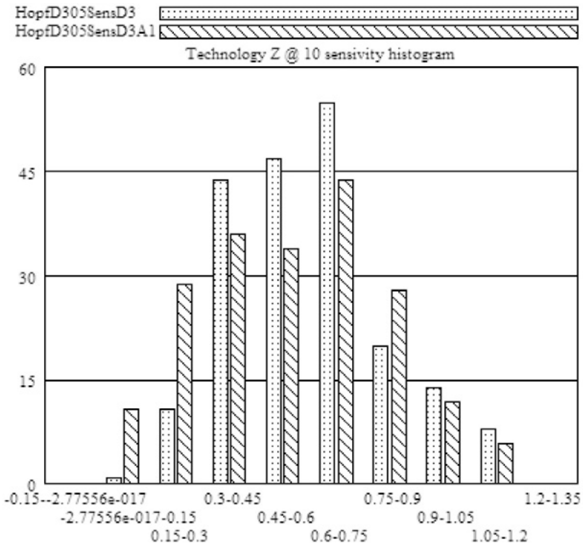

Fig. 20. Typical sensitivity histogram for Technology Z under combined uncertainty of diffusion coefficient A1 and interaction coefficient D3 at year 10 compared to uncertainty of interaction coefficient D3 only (cases 2 and 3).

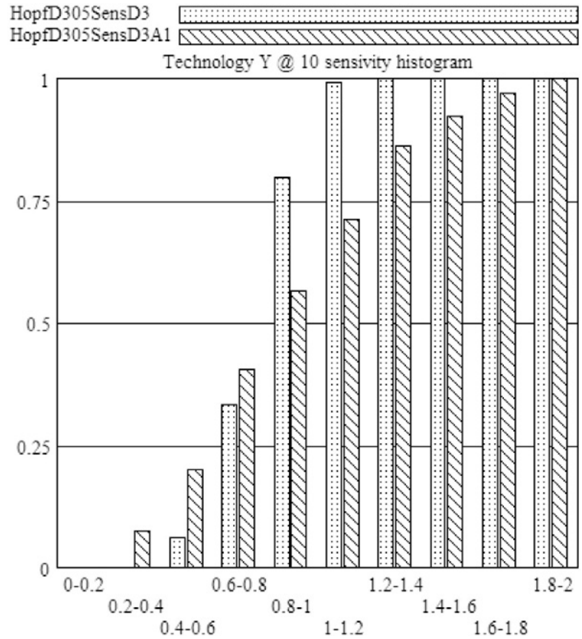

Fig. 21. Typical sensitivity cumulative distribution function for Technology Y under combined uncertainty of diffusion coefficient A1 and interaction coefficient D3 at year 10 compared to uncertainty of interaction coefficient D3 only (cases 2 and 3).

simulated diffusion parameter (A1) is symmetrical, the simulated technology histogram for the first technology (X) is skewed at time 20 years.

Simulation results for case 2 under uncertainty of policies again reinforce the concept of holism in technology management and is specifically useful for technology managers in practise: what happens in one part of a system (in this case interaction parameter D3 and Technology Z) tends to affect the entire system (here, for example, the relatively large range of uncertainty in Technology Y). Simulation results presented for case 3 support the idea that combination of uncertainties in the technology system tends to change the skewness of resulting technology level histograms. See, for instance, the change in histogram profile for Technology Y under combined uncertainty.

These results for uncertainty of parameters have specific practical technology risk management implications for the technology system considered. This implies that the system dynamics model developed may be used as technology risk management tool in, for instance, product development projects. This usefulness of the technology system dynamics model in technology risk management has furthermore been demonstrated for all three cases with simulated cumulative probability density function Technology X and Technology Y results during cyclic behaviour.

A real technology, industrial robot technology, has been found for which patent and publication data from bibliometrics indicated oscillatory behaviour over a period of approximately 15 years. This technology behaviour described in detail by Schmoch (2007) has been successfully compared to current technology system dynamics simulation results. Qualitative agreement has been found between real and simulated data again establishing confidence that certain technologies exhibit cyclic behaviour that may be modelled successfully using a system dynamics approach.

Another real technology associated with lasers in manufacturing has also been found in publication data from bibliometrics to show cyclic behaviour over a period of approximately 7 years. This further provides confidence in the technology system dynamics model in the sense that different periods of oscillations seem to occur in certain technologies. It has also been shown that this change in period of oscillation may be captured in the technology system dynamics model by changing, for instance, the diffusion coefficient A1 associated with Technology X.

Table 3
Some typical simulated model comparative uncertainty statistics at time year 10 (case 2 and 3).

Variable	Count	Min	Max	Mean	Median	SD	(Norm)
Technology X for D3	200	0.299	0.667	0.433	0.421	0.075	0.174
Technology X for D3 and A1	200	0.289	1.27	0.494	0.455	0.148	0.3
Technology Y for D3	200	0.503	1.23	0.868	0.87	0.155	0.178
Technology Y for D3 and A1	200	0.232	1.87	0.957	0.939	0.398	0.415
Technology Z for D3	200	0.148	1.17	0.604	0.589	0.217	0.359
Technology Z for D3 and A1	200	0.068	1.15	0.55	0.54	0.255	0.464

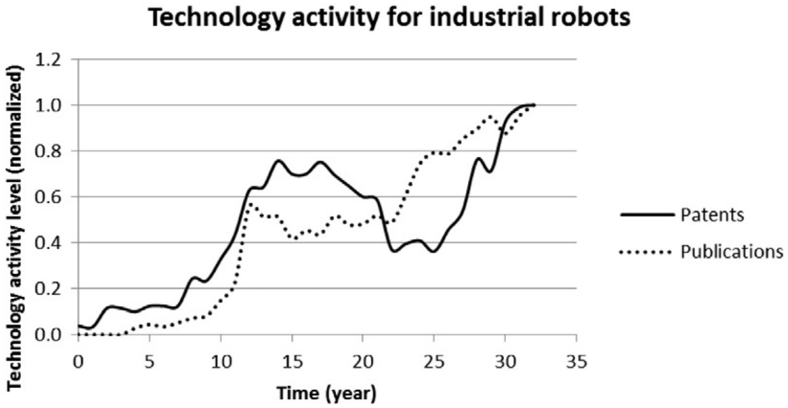

Fig. 22. Typical technology activity for industrial robots adapted from Schmoch (2007).

The exploratory research and case base method has been shown to be useful to establish the effectiveness of a system dynamics approach to model competing technology system behaviour. Here the simulated responses obtained using the technology system dynamics model were compared using bibliometrics data for at least two cases of real technologies displaying evidence of cyclic behaviour.

It should however be realized that not all technologies exhibit cyclic behaviour as pointed out by Schmoch (2007) and also illustrated in this paper where simulations of technology behaviour have been shown to be highly case and system structure or parameter dependent. The system dynamics model presented in this paper should then be interpreted on a case by case method and the model parameters adjusted accordingly. At this stage, the technology system dynamics model has been evaluated for two technology cases only based on bibliometrics data.

Future research may include identifying and simulating additional real cases where technologies exhibit cyclic behaviour. The modelling and simulation may include the effect of cyclic behaviour during technology growth towards a saturated market. The stock exchange using technology financial stock data as a proxy for technology behaviour as well as publication and patent data bases may be explored as a possible source of case data. The effect of uncertainty in other system parameters including those that may possibly lead to chaotic technology system behaviour may also be explored.

Furthermore, it may be useful to address the manner in which system dynamics can be used in combination with scenario analysis for improving technology forecasts in, for example, energy technology deployment across international borders analogous to say the work of Wang and Lan (2007) on technology substitution and scenarios. It may also be insightful to extend the research on the current system dynamics model to capture in some sense the behaviour of the third Technology Z as playing the role of supporting organisation or project team culture where two different interacting technologies are developed. This may have implications in, for instance, the perennial centralising or decentralising argument in technology organisations.

Argyres and Silverman (2004), for example, find evidence that organisations that have centralised research and development activities are more prone to follow research and development opportunities that may have enhanced impact on technological development in the future of their organisations. At the same time Rozemeijer (2000) reports on financial

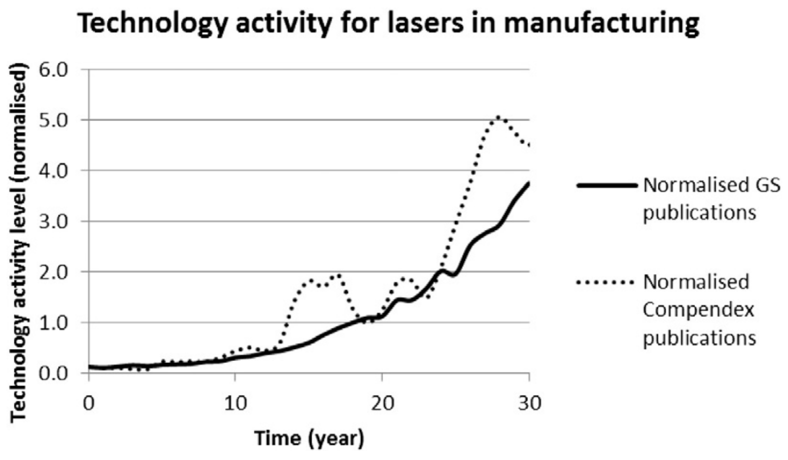

Fig. 23. Typical technology activity for lasers in manufacturing for a 30-year period.

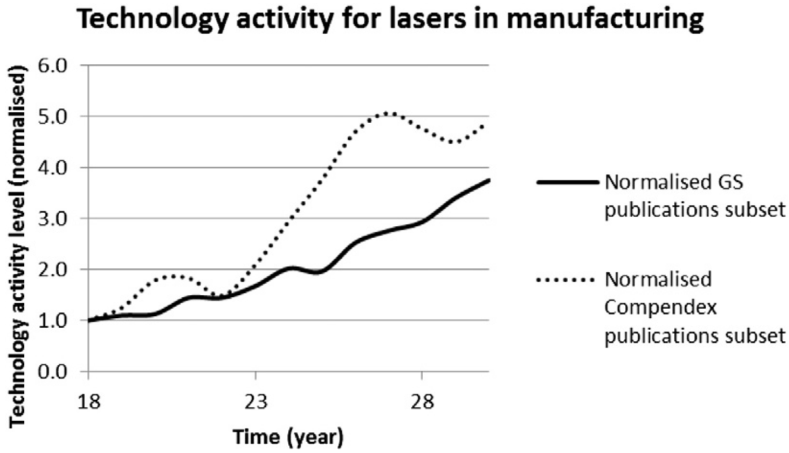

Fig. 24. Typical technology activity for lasers in manufacturing for a 12-year period.

services and pharmaceutical companies that are pursuing company-wide decentralisation processes.

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References

Ahmadian, A., 2008. System dynamics and technological innovation system models of multi-technology substitution processes. Masters degree dissertation ESA Report No. 2008:15. Chalmers University of Technology, Goteborg, Sweden.
Argyres, N.S., Silverman, B.S., 2004. R&D, organization structure, and the development of corporate technological knowledge. Strat. Manag. J. 25, 929–958.
Bae, J., Seetharaman, K., Suntharasaj, P., Ding, Y., 2007. Technology forecasting of RFID by using bibliometric analysis and Bass diffusion model. Proc. PICMET 2007, Portland, Oregon, USA, pp. 1637–1642 (5-9 August).
Bass, F.M., 2004. A new product growth model for consumer durables. Manag. Sci. 50 (12), 1825–1832.
Bauer, M., 1991. Resistance to change—a monitor of new technology. Syst. Pract. 4 (3).
Baxter, G., Sommerville, I., 2011. Socio-technical systems: from design methods to systems engineering. Interact. Comput. 23, 4–17.
Blin, F., Munro, M., 2008. Why hasn't technology disrupted academics' teaching practices? Understanding resistance to change through the lens of activity theory. Comput. Educ. 50, 475–490.
Chauvet, E., Paullet, J.E., Previte, J.P., Walls, Z., 2002. A Lotka–Volterra three-species food chain. Math. Mag. 75 (4), 243–255.
Cooper, D.R., Schindler, P.S. (Eds.), 2006. Business Research Methods, ninth edition McGraw-Hill.
Forrester, J.W., 1971. World dynamics. Wright-Allen Press.
Forrester, J.W., 1991. System dynamics and the lessons of 35 years. http://sysdyn.clexchange.org/sdep/papers/D-4224-4.pdf (accessed 01/04/2009).
Franz, C., Singpiel, H., Trein, J., 2011. Tracking the contour setup assistance, machine monitoring and process control for robot and scanner applications. LTJ 5 (September, www.laser-journal.deLTJ).
Heidrich, S., Richmann, A., Willenborg, E., 2011. Development of a Laser Based Process Chain for Manufacturing Freeform Optics. Phys. Procedia 12, 519–528.
Hunger, J.W., 1995. Engineering the System Solution: A Practical Guide to Developing Systems. Prentice Hall, New Jersey.
Jackson, M.C., 2003. Systems thinking: creating holism for managers. John Wiley & Sons, Chichester, West Sussex/Hoboken, N.J.
Kim, J., Lee, D.J., Ahn, J., 2006. A dynamic competition analysis on the Korean mobile phone market using competitive diffusion model. Comput. Ind. Eng. 51, 174–182.
Leedy, P.D., 2005. Practical Research: Planning and Design. Prentice Hall, Upper Saddle River, N.J.
Mamat, M., Mada, S.W.S., Salleh, Z., Ahmad, M.F., 2011. Numerical simulation dynamical model of three-species food chain with lotka-volterra linear functional response. J. Sustain. Sci. Manag. 6 (1), 44–50.
Mashayekhi, A.N., Ghili, S., 2010. System Dynamics Problem Definition as an Evolutionary Process Using Ambiguity Concept. http://www.systemdynamics.org/conferences/2010/proceed/papers/P1157.pdf (accessed 02/02/2013).
Meadows, D.H., 2008. Thinking in Systems: A Primer. In: Wright, D. (Ed.), Chelsea Green Publishing Company, White River Junction, Vermont.
Nair, A., Alsthom, D., 2003. Delayed creative destruction and the coexistence of technologies. J. Eng. Technol. Manag. 20, 345–365.
Potocan, V., Mulej, M., 2011. Managing organizational change as innovation. Proc. IHART 14 (available at www.intellectbase.org/e_publications/…/IHART_Spring_2011a.pdf (accessed 17/10/2013), 2011).
Pretorius, L., Pretorius, J.-H.C., 2010. A Systems Dynamics Case Study of Competing Optical Storage Technologies under Market Uncertainty. Proceedings of the 2010 IEEE ICMIT, June 2-5, Singapore, pp. 23–27.
Pretorius, L., Pretorius, J.H.C., 2012. A system dynamics approach to uncertainty in bridging technology Interaction. CIE42 Proceedings, 16-18 July 2012, Cape Town, South Africa © 2012 CIE & SAIIE, pp. 254-1–254-16.
Pretorius, L., Winzker, D.H., 2010. Biomedical Technology: A Case Study of Forecasting in Pulsed Electro Magnetic Field Therapy. PICMET 2010 Proceedings, July 18-22, Phuket, Thailand © 2010 PICMET.
Pretorius, L., Kruger, S., Benade, S.J., 2011. Technology diffusion and forecasting: the case of computational fluid dynamics (CFD) for simulation of greenhouse internal environments. Int. J. Innov. Technol. Manag. 8 (1), 27–39.
Pretorius, L., Pretorius, J.-H.C., Benade, S.J., 2012. Bridging technology under diffusion uncertainty: a systems dynamics case study. Proc. IAMOT 2012. Hsinchu, Taiwan (March 18-22).
Pretorius, L., Pretorius, J.H.C., Benade, S.J., 2013. A System Dynamics Approach to Technology Interaction Including Cyclic Behaviour. Proceedings of PICMET '13: Technology Management for Emerging Technologies, San Jose, USA.
Rozemeijer, F., 2000. How to manage corporate purchasing synergy in a decentralised company? Towards design rules for managing and organising purchasing synergy in decentralised companies. Eur. J. Purch. Supply Manag. 6, 5–12.
Schmoch, U., 2007. Double-boom cycles and the comeback of science-push and market-pull. Res. Policy 36, 1000–1015.
Vensim Software, 2012. http://www.vensim.com/ (accessed 01/04/2012).
Wang, M.Y., Lan, W.T., 2007. Combined forecast process: combining scenario analysis with the technological substitution model. Technol. Forecast. Soc. Chang. 74 (3), 357–378. http://dx.doi.org/10.1016/j.techfore.2005.08.002 (http://www.sciencedirect.com/science/article/pii/S0040162505001186).
Werthen, J., 2011. Trends in Solar Cell Technologies and Laser Manufacturing. LTJ (No. (1)) (www.laser-journal.deLTJ).
Wolstenholme, E.F., 1990. System Enquiry: A System Dynamic Approach. Wiley, Chichester.

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