PREDATOR–PREY ANALYSIS USING SYSTEM DYNAMICS: AN APPLICATION TO THE STEEL INDUSTRY

Douglas John Crookes*

Department of Economics, University of Pretoria

James Nelson Blignaut

Department of Economics, University of Pretoria and South African Environmental Observation Network, Pretoria

Accepted: October 2016

Abstract

In this paper, we use a predator–prey model to simulate intersectoral dynamics, with the global steel sector as the prey that supplies inputs and the automotive sector as the predator that demands its inputs. A further prey, an additional upstream supply sector, namely the iron ore sector, is added to reflect the implications of scarcity and resource limitations for industrial development and economic prospects. We find that capacity constraints in the steel industry could limit the future supply of vehicles, a result exacerbated by the unsustainable use of iron ore reserves. The solution is not for marginal steel industries to close, but for steelmakers to adapt and move to less resource-demanding secondary steelmaking technology rather than focusing on primary steelmaking. The forecasting capabilities of the model are compared with the outputs from a neural-network model. Although the results are comparable over the short term (±10 years), over the long term, results diverge, showing that forecasting steel-industry dynamics is complex and that further work is required to disentangle the drivers of supply and demand. This study indicates the potential advantages of using predator–prey models in modelling the supply chain in economics.

Key words: predator–prey, steel, vehicles, iron ore, system dynamics, neural network, Vensim

JEL: C6, D2, Q3

1 Introduction

Vehicles are ubiquitous. A recent article by Gross (2016) estimates that, by 2030, there will be two-billion automobiles on the roads, double the number in 2010. According to Gross, such growth is due largely to the growth in vehicle ownership in the developing world. This has consequences for climate change, as well as for public health and safety, and gives rise to environmental concerns relating to acid rain and congestion. As a result, the author raises concerns over the "epidemic spread of vehicle traffic" (Gross, 2016:309). The rise in vehicle traffic has implications for the availability of raw materials and requires further investigation. This is the focus of the present research. The effect of rising vehicular traffic meant that the global steel industry experienced significant growth in the past. This has continued in spite of the financial crisis. Production grew by, on average, 6.35 per cent year on year between 1998 and 2007, and, although production has fallen since the financial crisis, growth has remained at 3.33 per cent on average per annum. This is in spite of low profitability threating to close certain plants (Bowler, 2016). To put this growth in context, average growth of the steel industry was just over 5 per cent per annum between 1998 and 2014. In contrast, world agriculture grew by less than half of this, at an average of 2.49 per cent per annum year on year. Even with dampened demand for steel following the financial crisis, production growth remains strong in relation to other sectors.

Although the automotive sector is not the only destination for steel products, it is nonetheless important, constituting approximately 15 per cent of total global steel demand in 2007 (OECD, 2009). Trends in this sector are therefore important in determining the future supply of steel. Conversely, constraints in respect of steel production could also adversely affect the automotive

How to cite DOI: http://dx.doi.org/10.17159/2222-3436/2016/v19n5a4
ISSN: 2222-3436

industry. Vehicle production remained almost unchanged both before and after the financial crisis, with pre-2008 growth averaging 3.70 per cent and growth since 2008 averaging 3.47 per cent. Perhaps more importantly than its proportion of global steel demand is the fact that the automotive industry is a key indicator of economic welfare and progress. It will remain iconic to own a car going forward. As such, the automotive industry will continue to be a keystone and a trendsetting user of steel.

A predator–prey model is used to simulate intersectoral feedback dynamics between three sectors: the steel industry (the prey, which also acts as a predator with respect to resource use), a downstream sector (the automotive industry – the predator), and an upstream sector (the iron ore industry, the ultimate prey).

Although the predator–prey model was found to be suitable for use in system dynamics models (Swart, 1990), we found few explicit applications in the field of economics. One application that models business-cycle fluctuations is the Goodwin (1967) model. This model was developed as a system dynamics model by Weber (2005). Ecological applications of predator–prey models to system dynamics models abound (see e.g. Ford, 1999; Hannon & Ruth, 1997), and there are a number of other applications of predator–prey models, for example to policing (see e.g. Kim & Kim (1997) for interactions involving traffic police) and to a fishery (Crookes, 2016). Nasritdinov and Dalimov (2010), although not using a system dynamics model, are the first known to use a predator–prey model to simulate interactions between different sectors in a supply chain. In this paper, we wish to extend their model by including an environmental sector (iron ore) and using system dynamics modelling to explore the dynamics of industrial production and its effect on the environment. The model is novel in that a neural network is then used to test the forecasting capabilities of the system dynamics model.

This paper endeavours, firstly, to propose a method for enhancing the forecasting ability of system dynamics models by comparing the outcome with a neural-network model. Secondly, it highlights the policy implications of the findings for the steel industry in order to maximise sustainability in the sector, as well as in respect of upstream and downstream industries.

In the next section, we discuss the steel sector and why it is important to study it at this time. Thereafter, the predator–prey model is introduced and an explanation of system dynamics modelling and neural networks is given. The results of different simulations are then presented, along with a number of conclusions.

2 Methods

2.1 The predator–prey model

The predator–prey model, also known as the Lotka–Volterra model, simulates interactions in the following dynamical system,

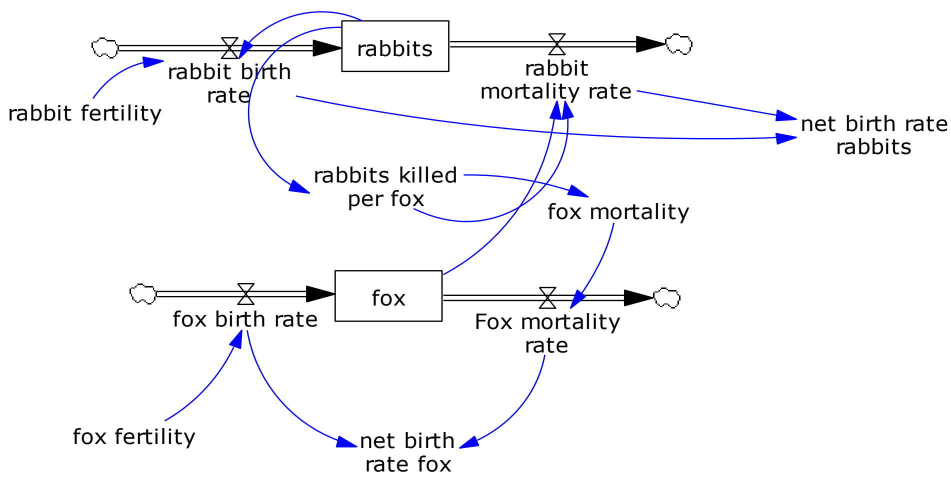
$$\frac{dx}{dt} = \varphi x - \delta xz$$

$$\frac{dz}{dt} = \mu xz - \tau z$$

where z is the predator population and x is the prey population. The predator–prey model, although relatively simple, provides a surprisingly complex range of dynamic behaviour from convergence to equilibrium, stable oscillations and corner solutions. (The equilibrium points are found by setting dx/dt=0 and dz/dt=0.) A simple stock-flow diagram featuring rabbits as the prey and foxes as the predators (see Figure 1) indicates what such a system might look like in Vensim.

Although Samuelson (1971) opened the door for the use of predator–prey models in economics, their potential has not yet been fully realised. Nasritdinov and Dalimov (N&D) (2010) present a seminal article in this regard whereby they simulate the interactions between the steel industry and the automotive industry using a predator–prey model. They develop the concept of a trophic function, which is the capability of a predator population to process the supply it receives from the prey population. Their model uses the predator–prey model to obtain a proxy for this trophic function; in other words, the model solves for the trophic function. Here, we extend their model, but, instead of solving for the trophic function, we incorporate a functional form that allows us to estimate the trophic function and then model the ensuing dynamics between predator and prey population. We also add a third downstream sector, the iron ore sector, which did not form part of the N&D model, in order to consider the effects of the availability of factors of production on the steel industry. Our model also has the benefit of including prices and costs of the predator and prey sector in the model, which is also not a feature of the N&D predator–prey model. These modifications enable us to consider the dynamics of the system over time, which was not possible in the N&D model, in order to make policy recommendations for the improvement of the sector. Finally, we compare the dynamics of the predator–prey system with forecasts generated by a neural-network model. In the next subsection, we consider the first of these modelling approaches, namely the system dynamics modelling approach.

Figure 1
Simple predator–prey system in Vensim



2.2 System dynamics modelling

System dynamics modelling was pioneered by Jay W Forrester in the 1950s. Early applications were in the field of management science (Forrester, 1961). Modelling the supply chain has a rich history in system dynamics (e.g. Sterman, 1989), although most of these involve applications to decision making in organisations. There are few, if any, explicit system dynamics applications using the predator–prey model in the economic sciences. System dynamics modelling is nonetheless an appropriate tool for modelling economic problems (Crookes & De Wit, 2014).

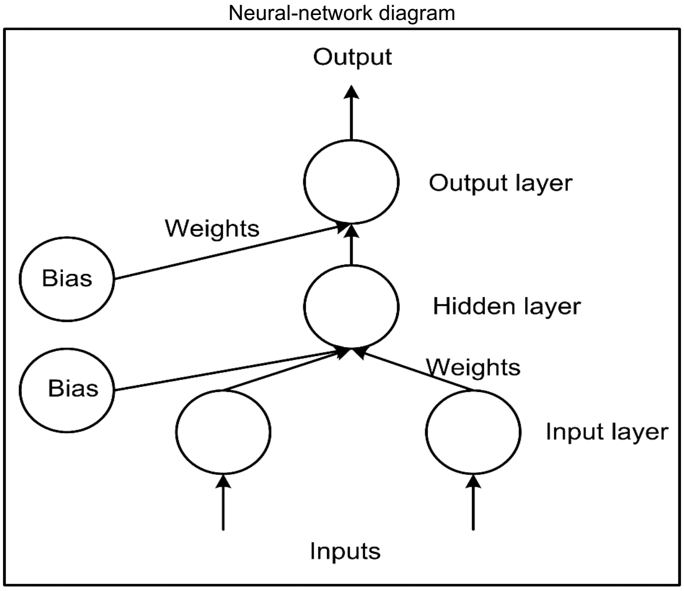
System dynamics modelling is the ideal tool for modelling intersectoral dynamics. Firstly, system dynamics is suitable for modelling feedback in the system. Secondly, although the basic framework models three sectors (the steel sector itself, an upstream sector and a downstream sector), there is potential in system dynamics modelling for adding a large number of interacting sectors (predator–prey systems). Thirdly, system dynamics models provide a means of estimating unknown parameter values using optimisation. This is known as “model calibration”. Fourthly, system dynamics models also provide advanced tools to validate models. A number of tools for model validation that are built into system dynamics modelling packages such as Vensim include tests of dimensional (units) consistency, extreme value tests (Reality Check in Vensim), and sensitivity analysis. These advantages make system dynamics modelling a preferred tool for modelling complex systems compared with pure spreadsheet modelling. System dynamics is now compared with another tool used for modelling, namely neural networks. In the next subsection, we consider our hybrid approach to simulation using neural networks.

2.3 Neural networks

In this model, system dynamics is used not only as a decision-support tool to answer "what if" types of questions, but also to forecast future steel availability. Given the concerns over the forecasting capabilities of system dynamics models (Butterworth, Plagányi, Robinson, Moosa & De Moor, 2015), we compare the results from the system dynamics model with a simple neural-network (NN) model. Neural networks are used for prediction and clustering (Warner & Misra, 1996). Rabelo, Helal and Lertpattarapong (2004) use the clustering approach to classify outputs from a system dynamics model using neural networks. Here, we use neural networks as a forecasting tool. In forecasting, neural networks act as a non-parametric regression model, enabling the simulation of more complex functional forms than standard linear regression (Warner & Misra, 1996).

There is some debate in the literature on whether or not neural networks provide a better forecast than linear models. A number of studies, reported in Tseng, Yu and Tzeng (2002), suggest that neural networks tend to outperform autoregressive integrated moving average (ARIMA) time-series models, particularly over longer forecast periods (see e.g. Maier & Dandy, 1996). De Gooijer and Hyndman (2006), on the other hand, conclude that "there are many outstanding issues associated with their use and implementation, including when they are likely to outperform other methods" (Gooijer & Hyndman, 2006:462). In spite of uncertainties, research shows that neural networks have great potential as a forecasting tool (Zhang, 2003). A three-layer, feedforward neural network trained using back propagation (Kaastra & Boyd, 1996) was constructed, with two inputs, one output and one hidden layer (see Figure 2). Ten per cent of the data was used for validation, and 50 iterations (epochs) were used for the training and validation. Profile plots for predicted steel were compared with the predictions from the system dynamics (SD) model. In the next section, we consider the model equations.

Figure 2
Neural-network diagram



Source: Adapted from Kaastra and Boyd (1996)

3 Steps in the modelling process

Following Sterman (2000), we adopt the following steps in the modelling process: articulation of the problem, formulating a dynamic hypothesis, formulating a simulation model, testing, and policy design and evaluation. In view of space constraints, each of these steps is discussed only briefly.

3.1 Articulation of the problem

Given the constraints on steel production and the "dirty" nature of such production, we wish to assess the effect of sustained vehicle demand on, firstly, the supply of steel, and, secondly, on the duration of iron ore reserves. This assessment is undertaken with reference to the different steelmaking technologies.

Generally speaking, one of three main technologies can be used in the production of steel. The first main technology option is that of primary steelmaking using basic oxygen furnaces (BOFs) that make use of iron ore as the primary input. The second main technology option is so-called secondary steelmaking that uses electric arc furnaces (EAFs) and recycled steel as the primary input. In 2007, the BOF and EAF methods were used to produce 66.3 per cent and 31.2 per cent, respectively, of the world's steel (World Steel Association, 2009). A third technology, namely steel production employing open-hearth furnaces (OHFs), produced just 2.5 per cent of steel in 2007, and its application continues to decline owing to its environmental and economic disadvantages (World Steel Association, 2009).

Iron ore, a key input of BOF steelmaking technology, is a limited resource. Lester Brown, in his book, *Plan B 2.0: Rescuing a planet under stress and a civilization in trouble*, published under the auspices of the Earth Policy Institute, estimates that the remaining iron ore reserves will last a mere 64 years, and this is based on a conservative estimate of growth in production (Brown, 2006; see, also, Crawford, 2011). This implies that iron ore reserves could be depleted by the year 2070. It is therefore important to examine the interactions between steel production, demand and iron ore use. Here, we define the BOF steelmaking technology as resource-depleting technology (RDT) in the sense that iron ore reserves are utilised, and the EAF steelmaking technology as resource-conserving technology (RCT) in that no iron ore is utilised in the production process (other resources such as coal and limestone are used, but in much lower quantities compared with the BOF steelmaking technology). In the next subsections, we discuss the theoretical underpinnings of the model.

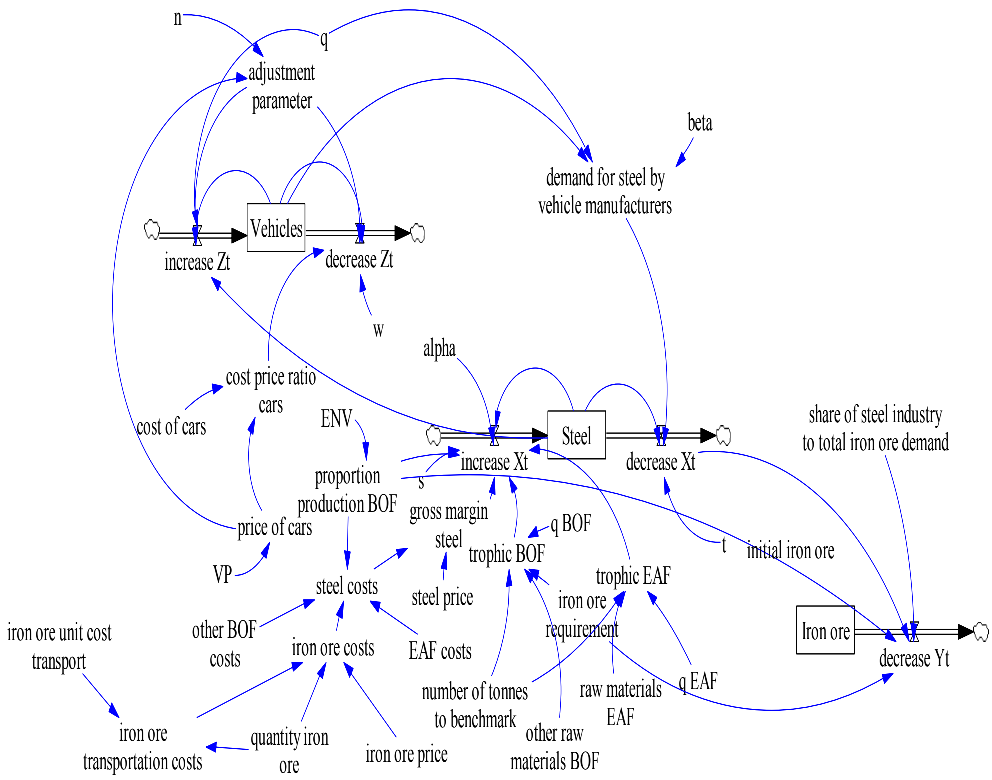
3.2 Formulation of a dynamic hypothesis

We hypothesise that increased vehicle demand will result in a "limit to growth" in the steel industry, resulting in capacity constraints. Influencing the way that steel is produced, it is hypothesised, will extend the useful life of raw materials used in the production process.

3.3 Formulating a simulation model

Here, we extend the predator–prey model of Nasritdinov and Dalimov (2010). The model is developed using the Vensim package. The stock-flow diagram for the model is given in Figure 3.

Figure 3
Stock-flow diagram for the steel model



A definition of all the exogenous variables in the model, and their parameter values, is given in Table 1.

Table 1
List of exogenous parameter values in the model

Parameter	Description	Value	Unit	Reference
n' =	Adjustment parameter for car-manufacturing sector	0.0042	cars/kt/year	Optimisation
c_z =	Cost parameter for car-manufacturing sector	30 044	dollars/cars	NA
p_z =	Price parameter for car-manufacturing sector	18 424 000	dollars/kt	Calculation
s =	Adjustment parameter for steel-industry growth	0.0268	1/year	Optimisation
t =	Adjustment parameter for withdrawals from steel industry	8e-005	1/year	Optimisation
w =	Proportion of production in downstream sector that is wasted	0.02	kt/cars	ND2010
k =	Capacity of steel production	914 504	Kt	ND2010 (calc.)
α =	Proportion of production spent on reproduction in the same sector	0.05	Dmnl	ND2010
β =	Proportion of demand by downstream sector for product from upstream sector (i.e. demand divided by total production)	0.94	Dmnl	ND2010 (average)
Y_I =	Quantity of iron ore used as input to steelmaking	1.4	tonne/tonne	WS
q_{YB} =	Conversion factor for BOF technology	0.38	1/kt	WS (calc.)
q_{YE} =	Conversion factor for EAF technology	1.04	1/kt	WS (calc.)

continued/

Y_b =	Other raw materials BOF	1.22	tonne/tonne	WS (calc.)
Y_e =	Raw materials EAF	0.96	tonne/tonne	WS (calc.)
p_x =	Price of steel	380	dollars/tonne	SB
γ_i =	Share of steel industry to total iron ore demand	0.07222	Dmnl	Optimisation
Y_{1998} =	Initial iron ore deposits	96 290 000	Kt	USGS (calc.)
X_{1998} =	Initial steel production	777 328	Kt	WS
Z_{1998} =	Initial cars produced	53 000 000	Cars	ND2010
c_B	Other steelmaking costs using BOF technology	220.04	dollars/tonne	Calculation
p_i	Iron ore price	51.63	dollars/tonne	SN
t_i	Iron ore unit cost of transport	5.8	dollars/tonne	SN
q_i	Quantity of iron ore	1.559	tonne/tonne	SN
c_E	Steelmaking costs, EAF technology	332.1	dollars/tonne	SN

Notes: Dmnl = dimensionless (no units); ND2010 = Nasritdinov and Dalimov (2010); NA = not used in model (no data); WS = data from World Steel; SB = steel benchmark (average of Nov. 2014 to Feb. 2016 price); USGS = 2014 reserves from US Geological Survey data – production data from model used to estimate 1998 values; SN = steel on the net.

The change in vehicle production (Z) over time is as follows:

$$\frac{dZ}{dt} = n'Z(q_z X - \frac{c_z}{p_z} - w)$$

Vehicle production is a function of profits as well as the costs of waste w. This formulation is based on an extension of the ND model in that it incorporates a profit function (first formulated by Wilen (1976), but used extensively in the fisheries and wildlife literature). Revenues from vehicle production are, in turn, a function of the quantity of steel supplied (X). The greater the availability of steel, the more vehicles that will be produced.

Steel production (X) also changes based on the profitability of the sector, but excess demand for steel reduces steel inventories, which places pressure on the sector to produce more:

$$\frac{dX}{dt} = sX[\alpha(p_x - c_x)V - \frac{t}{s}\beta q_z Z]$$

Here, V is the trophic function; in other words, it reflects the capability of the steel industry to process the supply of raw materials it receives.

In the model, $V = m_B*(Y_I+Y_b)*q_{YB}+m_E*Y_e*q_{YE}$, m_B is the proportion of steel production using BOF technology, Y_I is the iron ore requirement for BOF technology, Y_b is the other raw-material requirement for BOF technology, q_{YB} is a conversion factor from raw materials to steel using BOF technology, m_E is the proportion of steel production that is EAF, Y_e is the raw-material requirement for EAF technology, and q_{YE} is a conversion factor from raw materials to steel using EAF technology.

The costs of steel production (c_x) are calculated as follows:

$$c_x = m_B(p_i q_i + t_i q_i + c_B) + m_E c_E$$

Here, MB is the proportion of production that is BOF, p_i is the iron ore price, q_i is the quantity of iron ore, t_i is the iron ore unit cost of transport, q_i is the quantity of iron ore used, C_B is other steelmaking costs using the BOF technology, m_E is the proportion of production that is EAF, and c_E is the cost of EAF production. The final time of the simulation is 2100.

The change in iron ore reserves (Y) is affected by both the production of motor vehicles and the demand for iron ore by the steel industry:

$$\frac{dY}{dt} = -Y_I m_B t X q_Z Z/\gamma_i$$

Here, $Y_I m_B$ is the share of iron ore used in steel production, tXq_zZ is the quantity of steel demanded in a year, and γ_i is the share of steel iron ore demand to total iron ore demand.

The model has many potential applications. However, a constraint on its use in practice is the data-intensive nature of the model. For example, parameters such as the adjustment coefficient n' and the trophic function V are not easy to obtain from the literature. In this case, optimisation is used to estimate values for these parameters based on the best fit of the model. In the next subsection, various tests are conducted on the model in order to validate it.

3.4 Testing of the model

Testing of the model comprises three major components (Barlas, 1996): structure assessment tests, behaviour assessment tests and policy implication tests. Policy implication tests are rarely conducted, as they usually occur after the model has been completed (Winz, Brierley & Trowsdale, 2009). The main focus in testing the model is therefore on structure assessment tests and behaviour assessment tests.

The structure of the model is based on the well-established predator–prey model and is therefore regarded as robust. The parameters are derived from the literature through calculations or through calibration. All units in the model are consistent; in other words, the model passed the dimensional-consistency test. Reality Check was also conducted on extreme values in the model using the Vensim software. Four extreme values were tested. The first was that the costs were set at zero. This did not noticeably affect the dynamics of the model. It was therefore concluded that the model is not sensitive to changes in vehicle costs. Secondly, the structure of the model was tested by incorporating a density-dependent logistic term (see e.g. Milner-Gulland & Leader-Williams, 1992) instead of a profit function. This did not significantly affect the dynamics of the steel-industry stocks, so it was concluded that the profit specification was preferred. Thirdly, the adjustment coefficient, s, was tested for unity, and this significantly affected steel dynamics. The fourth reality check that was performed was to reduce β, the proportion of demand for steel from the car industry, from 0.94 to 0.05. The model performed as expected, with steel stocks increasing compared with the baseline.

The model therefore performed well both under extreme value tests of the model and under sensitivity analysis of a number of key variables. The model was less satisfactory at replicating the effect of the financial crisis on production, particularly for vehicle production, and this could overstate demand for steel from the automotive sector. However, on aggregate, the calibration provided a good fit with the historical data, both in terms of vehicle and steel production (see Table 1). For steel production, the data predicted an average growth of 5.03 per cent per annum year on year between 1998 and 2014, while the model estimated an average of 4.99 per cent growth per annum. Furthermore, vehicle-production growth was also comparable, with the data indicating an average year-on-year growth of 3.60 per cent between 1998 and 2014, and the model indicating an average growth of 3.45 per cent. The adjusted R^2 was 0.9688 for steel and 0.9062 for vehicles, respectively (see Table 2).

Table 2
Percentage change in production, pre- and post-financial crisis

	Steel			Vehicles			Agriculture
	Data	Model	Adj. R^2	Data	Model	Adj. R^2	Data[1]
1998-2007	6.35	5.40		3.70	2.85		2.51
2008-2014	3.33	4.45		3.47	4.21		2.47
Total	5.03	4.99	0.9688***	3.60	3.45	0.9062***	2.49

*Notes: Data = historical data; model = outputs from the SD model; Adj. R^2 = comparison between data and model; *** P-values: P<0.0001.*

[1]Agriculture production data are for the period from 1998 to 2013 (FAOSTAT).

The model is a partial disequilibrium model in the sense that variables outside the model are held equal (the ceteris paribus assumption). Although there is feedback in the model, with the result that the model is classified as a system dynamics model, the model has an extremely simplistic feedback loop. In spite of this, the model is able to replicate the historical data well so that the boundary of the model is deemed adequate.

The model was also tested for surprise behaviour. A survey by Ducker Worldwide found that automakers will increase their use of aluminium from 8 per cent of vehicle kerb weight in 2009 to 16 per cent by 2025 (Drive Aluminium, 2016). A simple model extension was therefore added to the model, with vehicle operational costs a function of the ratio of steel to aluminium used, and with the demand for steel dependent on the proportion of steel used. The model showed that an increase in aluminium use in vehicles reduced demand for steel in the short term. However, this resulted in an increase in steel stocks. Since demand for steel is a function of the available steel stock, overall demand for steel actually increased. This resulted in iron ore stocks depleting more rapidly than under the baseline. The model therefore showed that increased aluminium use could actually have an adverse effect on iron ore reserves. This was a surprising outcome of the model, and one that requires further investigation, but which does not form part of the final model simulations.

3.5 Policy design and evaluation

A baseline model and four sets of scenarios are adopted in this study. Parameter values used for the simulations are given in Table 3.

- Baseline = No change in parameters as summarised in Table 3
- Scenario 1 = Increase in production in the steel sector
- Scenario 2 = Reduction in the use of resource-depleting BOF technology and an increase in the use of resource-conserving EAF technology (Moderate ENV scenario)
- Scenario 3a = Extreme vehicle-price reduction (Extreme VP scenario)
- Scenario 3b = Moderate vehicle-price reduction (Moderate VP scenario)
- Scenario 4a = Extreme vehicle-price reduction and extreme reduction in BOF technology and increase in EAF technology (Extreme VP and ENV scenario)
- Scenario 4b = Moderate vehicle-price reduction and moderate reduction in BOF technology and increase in EAF technology (Moderate VP and ENV scenario)

Table 3

Scenarios used in the model and parameter values

Scenario	Name	Description	Variable changed	Baseline value	New value
1	Production increase	Increase in production in the steel sector	alpha	0.05	0.1
2	Moderate ENV	Reduction in use of BOF technology; and Increase in use of EAF technology	m_B m_E	0.7 0.3	0.4 0.6
3a	Extreme VP	Extreme vehicle-price reduction	γp_z	$\gamma = 1$	$\gamma = 0.1$
3b	Moderate VP	Moderate vehicle-price reduction	γp_z	$\gamma = 1$	$\gamma = 0.5$
4a	Extreme VP and ENV	Extreme vehicle-price reduction; and Extreme reduction in BOF technology and increase in EAF technology	γp_z m_B m_E	$\gamma = 1$ 0.7 0.3	$\gamma = 0.1$ 0.1 0.9
4b	Moderate VP and ENV	Moderate vehicle-price reduction; and Moderate reduction in BOF technology and increase in EAF technology	γp_z m_B m_E	$\gamma = 1$ 0.7 0.3	$\gamma = 0.5$ 0.4 0.6

4 Results

4.1 Baseline

The model indicates that, at current rates of (increasing) demand by the automotive industry, steel inventories could be depleted by the year 2070 (see Figure 4a, the dark lines). Similarly, iron ore stocks will be depleted by 2070 (see Figure 4b, the dark lines). This latter finding is consistent with the estimates of Brown (2006). In the model, it is actually a lack of capacity to produce sufficient steel to meet demand for steel by the automotive industry which is driving stocks down. In the model, vehicle production increases more than eightfold by 2070 compared with 1998 production estimates (see Figure 4c, the dark lines). The simulations consider four solutions in order to attempt to increase stocks and result in a more long-term supply of both steel and iron ore.

4.2 Scenario 1: Increase production

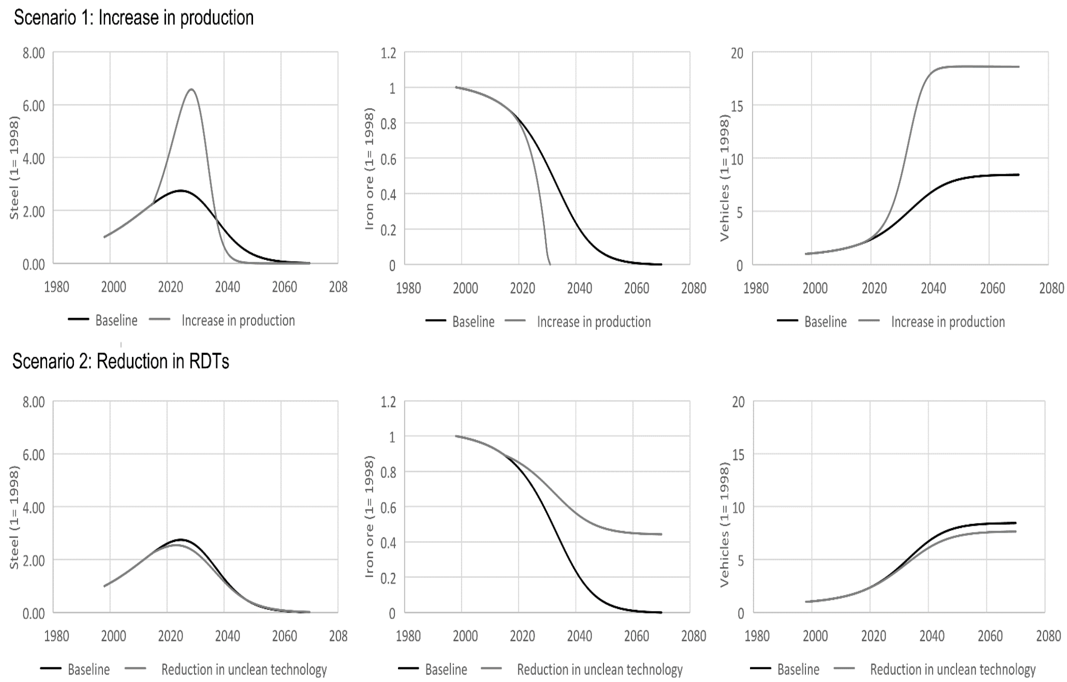
For the first set of simulations, steel production is doubled in 2015 from 5 per cent per annum to 10 per cent per annum in order to attempt to eliminate the lack of capacity (see Figure 4.1a). The result is that vehicle production also increases – to more than 18 times 1998 values (see Figure 4.1c). This results in greater demand for iron ore deposits, leading to the depletion of reserves by around 2030 (see Figure 4.1b). Therefore, the net effect of increasing production is that iron ore reserves will be depleted.

4.3 Scenario 2: Switch to resource-conserving technologies (RCTs)

The cleaner-technology scenario involves a reduction in the use of the BOF method from 70 per cent of total production to 40 per cent of production and an increase in the use of the resource-conserving EAF technologies from 30 per cent to 60 per cent of total production (Moderate ENV scenario). This has a relatively insignificant effect on steel production (see Figure 4.2a) and vehicle manufacturing (see Figure 4.2c), with each showing a slight decline compared with the baseline. The reason for this decline is largely due to the increase in steelmaking operational costs, as the EAF technology is slightly more expensive. The most significant difference noticeable in the switch to RCTs is the improvement in the persistence of iron ore reserves. By 2070, iron ore reserves are slightly less than 50 per cent of 1998 estimates and remain fairly flat (see Figure 4.2b). However, over the long term, the steel industry still experiences capacity constraints in meeting the growing supply of motor vehicles. The next scenario considers how to reduce the production of motor vehicles.

Figure 4

Policy scenarios 1 and 2 for, from left to right, a) steel, b) iron ore and c) vehicles



4.4 Scenario 3: Reduce the price of vehicles

The supply of motor vehicles continues to increase owing to the low cost of steel. The solution is a demand-reduction strategy modelled by reducing the price of vehicles (VP). The effect is to reduce profitability in the sector, which contracts vehicle production. This scenario models two reductions in vehicle prices, the first to 10 per cent of original values (Extreme VP scenario), and the second to 50 per cent of original values (Moderate VP scenario). Figure 5.3a shows that steel stocks increase under both scenarios compared with the baseline, with the 50 per cent price scenario producing a steel stock of approximately 30 per cent of 1998 estimates by 2070. Vehicle manufacturing increases, but at a slower rate than under the baseline (see Figure 5.3c). Iron ore stocks, one the other hand, are worse off than under the baseline (see Figure 5.3b), with depletion occurring between 2045 and 2050, depending on the scenario, compared with 2070 in the baseline. This suggests that the switch to RCTs is crucial. A final scenario is therefore considered.

4.5 Scenario 4: Reduce the price of vehicles and switch to RCTs

The final set of scenarios model both a reduction in the price of motor vehicles along with a shift to RCTs. In the first scenario, an extreme environmental and vehicle-price reduction scenario is modelled (Extreme VP and ENV scenario) where the proportion of steelmaking using the BOF technology is reduced to 10 per cent (compared with a baseline of 70 per cent), the proportion of the resource-conserving EAF technologies is increased to 90 per cent, and the price of vehicles is reduced to 10 per cent of original values. In the second scenario, a more moderate environmental and vehicle-price scenario is implemented, with the vehicle price reduced to 50 per cent of original values and the proportion of steelmaking using BOF technologies reduced to 40 per cent, while the proportion of steelmaking using the resource-conserving EAF technologies is increased to 60 per cent of production (Moderate VP and ENV scenario).

Steel inventories improve under both scenarios: for the extreme VP and ENV scenario, they increase to just under 3.5 times 1998 values by 2070, and, even under the moderate VP and ENV scenario, stocks are 30 per cent of original values, which is a considerable improvement compared with the baseline (see Figure 5.4a). Iron ore reserves also improve considerably compared with the baseline, ranging from around 30 per cent of 1998 values for the moderate VP and ENV scenario to 75 per cent of 1998 values for the extreme VP and ENV scenario (see Figure 5.4b). As expected, vehicle production decreases compared with the baseline, but still increases compared with 1998 values. By 2070, vehicle production is just over 2.5 times 1998 production under the extreme VP and ENV scenario, and almost six times 1998 production under the moderate VP and ENV scenario (see Figure 5.4c).

4.6 Forecast validation

The baseline SD model predicted that steel inventories would peak in around 2025, followed by a decline by 2070 (e.g. Figures 4a). We forecast projected steel inventories using a NN model (2015-2035), and then compare the forecasted steel inventories from the SD and NN models using the adjusted R^2 statistic (see Figure 6). The SD and NN models produce the same dynamic pattern over the short term (±10 years), with steel inventories increasing initially and then levelling off. The correlation between the steel-inventory predictions from the NN and SD models are above 0.99 between 2015 and 2026, whereafter they begin to fall (see Figure 6). This is because the NN model and the SD model begin to diverge, with the NN predicting a fairly flat steel inventory beyond 2025 and the SD model predicting a rapid decline in inventories. Caution should therefore be exercised in interpreting the longer-term results from the model. Additional research is required to further disentangle the dynamics of supply and demand in the steel industry, particularly over the longer term.

Figure 5

Policy scenarios 3 and 4 for, from left to right, a) steel, b) iron ore and c) vehicles

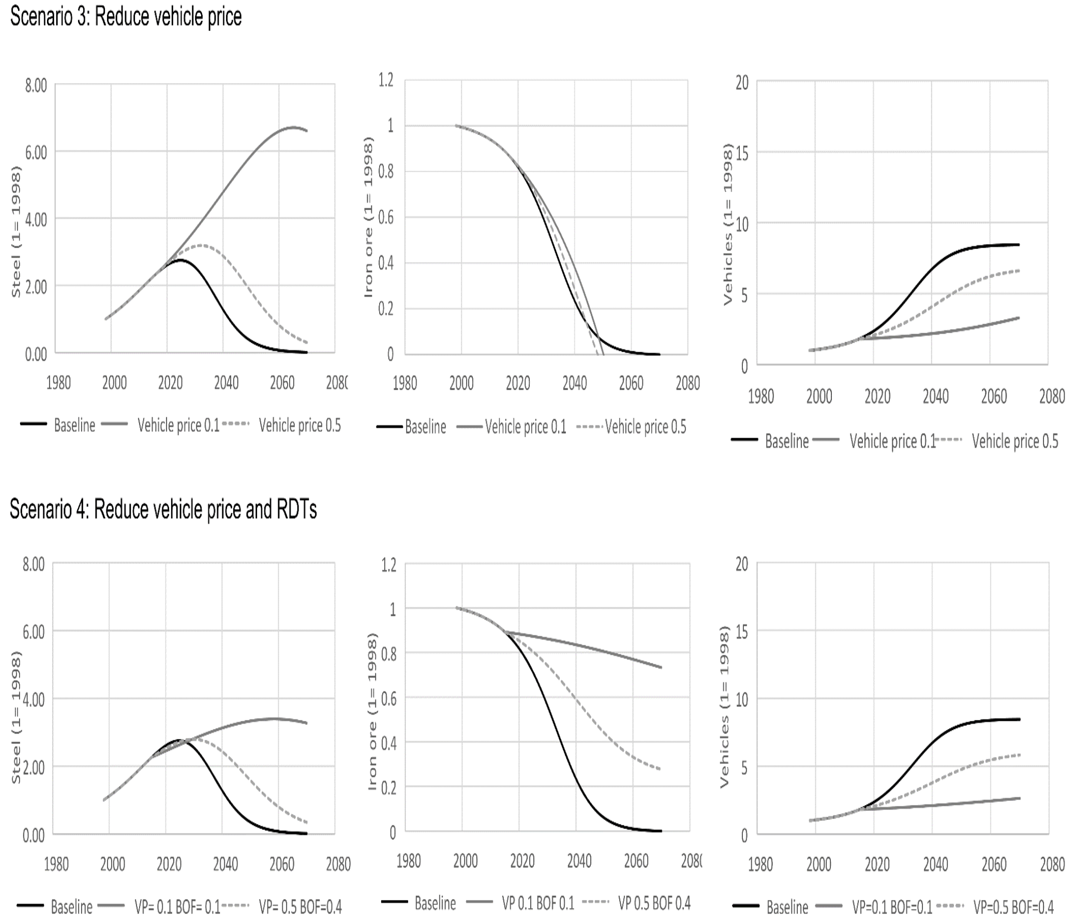
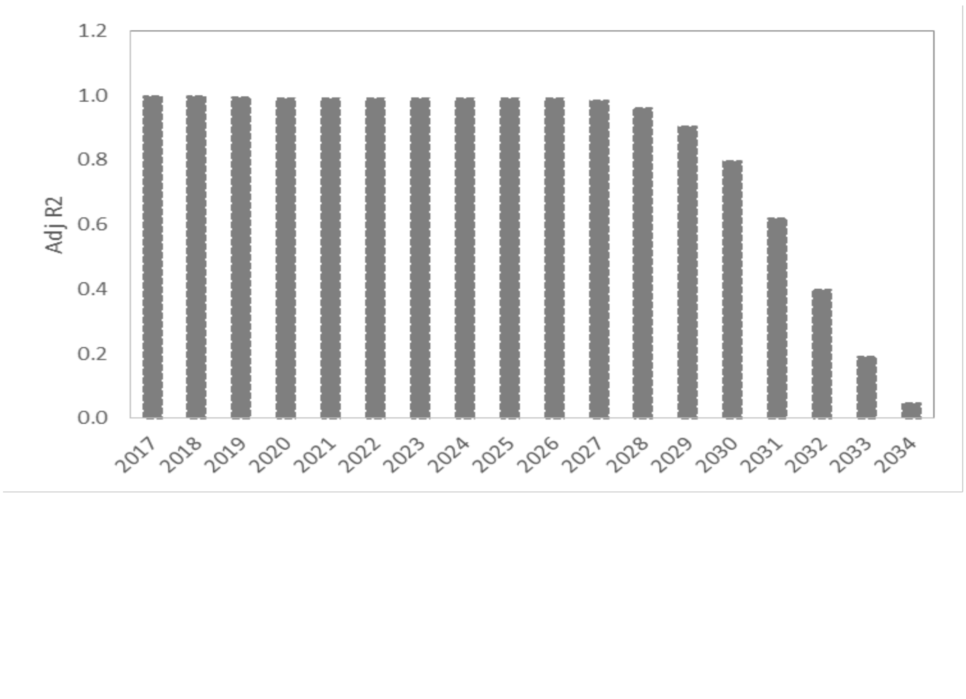


Figure 6

Correlation (adjusted R-squared value) between the system dynamics (SD) and neural-network (NN) forecast of steel inventories



5 Conclusions

Negative-feedback models such as the predator–prey model indicate that there are limits to growth. Even with technological advances, supply cannot continue unabated. These types of models will not be applicable in all instances, but should rather be used when there is some form of resource constraint. In this case, iron ore availability acted as a constraint to future expansion of the steel sector. The solution is for the sector to switch to the more environmentally sustainable EAF technology.

The boom days of the steel sector meant that excess capacity existed. However, with the falling price of steel, a number of industries are at risk of closing. The low price of steel also means that there is a higher demand for steel by the automotive industry. These two factors combined mean that there is a risk of falling steel inventories in the future. One solution is to reduce the demand for steel in the automotive sector, for example by promoting the switch to public transport. This is equivalent to reducing the price of vehicles in the model. Steel-producing industries that are experiencing profitability constraints should not close, as excess demand implies that the supply of steel could also rebound in the future – in which case, additional capacity would be required. Again, however, production at the higher output level would necessitate a switch to the more sustainable steelmaking technology. There is certainly potential for more marginal plants to utilise this technology, and even employ a form of "eco-labelling" (Blignaut & De Wit, 2004), which would allow them to differentiate themselves from their competitors and sell their steel at a premium to their clients. This would, however, require the development of an internationally recognised certification scheme for steel.

Predator–prey models have good potential for the analysis of intersectoral dynamics. In spite of the relative simplicity of the current model, there is potential to greatly expand their use to other sectors, factors, and household demand sectors.

Endnote

Correspondence to: d_crookes@hotmail.com

References

BARLAS, Y. 1996. Formal aspects of model validity and validation in system dynamics. *System Dynamics Review*, 12(3):183-210.

BLIGNAUT, J.N. & DE WIT, M. 2004. *Sustainable options: Development lessons from applied environmental economics*. Cape Town: UCT Press.

BOWLER, T. 2016. Britain's steel industry: What's going wrong? BBC News. 30 March 2016. Available at: http://www.bbc.com/news/business-34581945 [accessed April 2016].

BROWN, L.R. 2006. *Plan B 2.0: Rescuing a planet under stress and a civilization in trouble*. New York: WW Norton.

BUTTERWORTH, D.S., PLAGÁNYI, É.E., ROBINSON, W.M.L., MOOSA, N. & DE MOOR, C.L. 2015. Penguin modelling approach queried. *Ecological Modelling*, 316:78-80.

CRAWFORD, R.H. 2011. *Life cycle assessment in the built environment.* London: Spon Press.

CROOKES, D.J. 2016. Trading on extinction: An open-access deterrence model for the South African abalone fishery. *South African Journal of Science*, 112(3/4):105-113.

CROOKES, D.J. & DE WIT, M.P. 2014. Is system dynamics of relevance to neoclassical economists? *South Africa Journal of Economics*, 82(2):181-192.

DE GOOIJER, J.D. & HYNDMAN, R. 2006. 25 years of time series forecasting, *International Journal of Forecasting*, 22(3):442-473.

DRIVE ALUMINIUM. 2016. Vehicle uses – aluminium use grows; steel continues to lose vehicle market share. Available at: http://www.drivealuminum.org/vehicle-uses [accessed April 2016].

FORD, A. 1999. *Modeling the environment*. Washington, DC: Island Press.

FORRESTER, J. 1961. *Industrial dynamics*. New York: MIT Press & John Wiley & Sons.

GOODWIN, R.M. 1967. A growth cycle. In C.H. Feinstein (ed.) *Socialism, capitalism and economic growth: Essays presented to Maurice Dobb*. London: Cambridge University Press.

GROSS, M. 2016. A planet with two billion cars. *Current Biology*, 26:R307-R318.

HANNON, B. & RUTH, M. 1997. *Modeling dynamic biological systems*. New York: Springer-Verlag.

KAASTRA I. & BOYD, M. 1996. Designing a neural network for forecasting financial and economic time series. *Neurocomputing*, 10:215-236.

KIM, D-H. & KIM, D.H. 1997. A system dynamics model for a mixed-strategy game between police and driver. *System Dynamics Review*, 13(1):33-52.

MAIER, H.R. & DANDY, G.C. 1996. Neural network models for forecasting univariate time series. *Neural Networks World*, 6 (5):747-772.

MILNER-GULLAND, E.J. & LEADER-WILLIAMS, N. 1992. A model of incentives for the illegal exploitation of black rhinos and elephants: Poaching pays in Luangwa Valley, Zambia. *Journal of Applied Ecology*, 29:388-401.

NASRITDINOV, G. & DALIMOV, R. 2010. Limit cycle, trophic function and the dynamics of intersectoral interaction. *Current Research Journal of Economic Theory*, 2(2):32-40.

OECD. 2009. *OECD Steel committee presentation for the council working party on shipbuilding*. 9 July 2009. Paris: Organisation for Economic Co-operation and Development.

RABELO, L., HELAL, M. & LERTPATTARAPONG, C., 2004. Analysis of supply chains using system dynamics, neural nets, and eigenvalues. In *Proceedings of the 2004 Winter Simulation Conference*, 1136-1144.

SAMUELSON, P.A. 1971. Generalized predator-prey oscillations in ecological and economic equilibrium. *Proceedings of the National Academy of Sciences of the United States of America*, 68:980-983.

STERMAN, J.D. 1989. Modeling managerial behavior: Misperceptions of feedback in a dynamic decision making experiment. *Management Science*, 35(3):321-339.

STERMAN, J.D. 2000. *Business dynamics: Systems thinking and modeling for a complex world*. Boston: Irwin/McGraw-Hill.

SWANSON, N.R. & WHITE, H. 1997. Forecasting economic time series using flexible versus fixed specification and linear versus nonlinear econometric models. *International Journal of Forecasting*, 13: 439-461.

SWART, J. 1990. A system dynamics approach to predator–prey modelling. *System Dynamics Review*, 6(1):94-99.

TSENG, F.M., YU, H.C. & TZENG, G.H. 2002. Combining neural network model with seasonal time series ARIMA model. *Technological Forecasting and Social Change*, 69:71-87.

WARNER, B. & MISRA, M. 1996. Understanding neural networks as statistical tools. *The American Statistician*, 50(4):284-293.

WEBER, L. 2005. A contribution to Goodwin's growth cycle model from a system dynamics perspective. Proceeds of the 23rd International System Dynamics Conference, Boston MA, 17-21 July.

WILEN, J.E. 1976. Common property resources and the dynamics of overexploitation: The case of the North Pacific fur seal. *University of British Columbia Resources Paper* No. 3, September 1976.

WINZ, I., BRIERLEY, G. & TROWSDALE, S. 2009. The use of system dynamics simulation in water resources management. *Water Resources Management*, 23:1301-1323.

WORLD STEEL ASSOCIATION. 2009. 2008 sustainability report. Available at: https://www.worldsteel.org/dms/internetDocumentList/bookshop/2008-Sustainability-Report/document/2008%20Sustainability%20Report.pdf [accessed April 2016].

ZHANG, G.P. 2003. Times series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing*, 50:159-175.