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Contributing to Knowledge-based Decision Support: A System Dynamics Model Regarding the Use of Non-renewable Resources

by

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CONTRIBUTING TO KNOWLEDGE-BASED DECISION SUPPORT: A SYSTEM DYNAMICS MODEL REGARDING THE USE OF NON-RENEWABLE RESOURCES

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Abstract

In dynamic business contexts where knowledge is continually evolving and thus critical for better organizational performance, not only knowledge re-use but also knowledge re-creation becomes more and more important. One of these contexts is the use of non-renewable resources in innovative high-tech products. Since media recently spread – often contradictory – news about the increasing scarcity of non-renewable resources, decision makers face a high degree of uncertainty. They struggle to understand and handle the information available. Therefore, it is essential to provide a methodological approach to externalize and combine expert knowledge of a system's inherent logic. Hence, in this paper we show that mental models of experts can be transformed into an explicit simulation model in order to support decision makers comprehending the short- and long-term dynamic interdependencies of the development of non-renewable resources on demand, supply, and price. For this purpose, we combine known cause-and-effect relationships into an integrated model using the system dynamics methodology. The application of the idea to capture knowledge in a simulation model is exemplarily instantiated with real-world information for the case of indium.

Keywords: System Dynamics, Knowledge Management, Non-renewable Resources, Decision Support Systems.

1 Motivation

Knowledge management has been defined as uncovering and managing different levels of knowledge from individuals, teams, and organizations in order to improve performance (Nonaka, 1994; Davenport et al., 1998). Especially in dynamic business contexts where knowledge is rapidly evolving, not only re-use but also re-creation of knowledge – i.e. the continual refresh of the knowledge base (Apostolou and Mentzas, 2003) – represents a substantial source of long-term competitive advantage. One particular dynamic context is the use of non-renewable resources in production companies. Since certain metals, rare earths and other non-renewable resources form an essential fundament for innovative high-tech products, their increasing scarcity recently became more and more important (European Commission, 2010). This can have significant impact on decisions to be made and thus on the sustainable success of the organization.

If, for instance, a research & development department needs to decide to what extent a certain non-renewable resource will be used in a new product, this design decision has far-reaching consequences for the whole life of the product. Potential subsequent design changes are not only time-consuming but can also turn out to be very expensive. For an adequate decision a comprehensive and evolving knowledge base is required. However, this is often challenging. Even though experts working in research & development get – often contradictory – pieces of information from internal (e.g. strategy department) and external (e.g. the media) sources, it is difficult not only to externalize and combine these new insights but also to re-create knowledge in order to address questions as:

- How to judge short-term and long-term consequences of a sudden significant supply drop (or increase) of a particular non-renewable resource? For example, latest news reports that China – accountable for 97% of the world's rare earths production (European Commission, 2010) – plans to reduce its exports of rare earths by up to 30% (Bradsher, 2010).
- To what extent would the existence of an appropriate substitute material impact the total demand of a particular non-renewable resource? Tantal – currently used in micro-capacitors – could be substituted by the explorative non-ferroelectric material $\text{CaCu}_3\text{Ti}_4\text{O}_{12}$ due to its immense advance in quality (Lunkenheimer et al., 2010).
- How does the price influence recyclability for a particular non-renewable resource? Even though indium – a rare metal – is not recycled so far, the USGS yearbook (Tolcin, 2009) states that “recent improvements to the process technology have made indium recovery from tailings feasible when the price of indium is high”.

Although such isolated influencing factors can be understood quite easily, their combined occurrence can result in shortcomings: Misperceptions of feedback, unscientific reasoning, judgmental biases, and defensive routines (Sterman, 2000; Wolstenholme, 2003) hinder a decision maker's ability to comprehend the structure and dynamics of complex systems. These difficulties are intimately connected with problems in the mental model (i.e. “conceptual representations of the structure of an external system used by people to describe, explain, and predict a system's behavior” (Capelo and Dias, 2009)) of the decision maker. In order to improve the individual mental model it is necessary to externalize the knowledge of the decision maker and combine it with the knowledge of experts in the organizational domain. Since these mental models have been central to system dynamics (SD) from the beginning of the field (Sterman, 2000; Wolstenholme, 2003), this methodological approach has been claimed to be able to manage and apply knowledge for better organizational decision making (Forrester, 1961; Senge, 1994).

Because literature also shows the acceptability of SD for analyzing time-continuous, short-term and long-term developments, and feedback loops, we investigate the following research question:

How can the development of a particular non-renewable resource be modeled by means of a SD model in order to support decision makers understanding the short- and long-term effects of resource depletion and resource recycling on demand, supply, and price?

The paper proposes to capture knowledge in a SD model. Section 2 gives an overview of related work and substantiates the research gap. Section 3 presents both structure and behavior of the model. Section 4 exemplarily applies the model to the non-renewable resource indium and shows how the model contributes to knowledge-based decision support by means of scenario analysis. Section 5 summarizes key findings, discusses limitations, and points out future research.

2 Related Work

2.1 Knowledge-based decision support using system dynamics

A general definition of decision support systems stems from Sprague (1980) who characterizes them as “interactive computer based systems, which help decision makers utilize data and models to solve unstructured problems”. As can be seen, this and similar definitions (e.g. March and Hevner, 2007) do not explicitly integrate the impact of knowledge on decision making. Even though several studies argue that knowledge represents an essential organizational capability (e.g. Nonaka, 1994; Grant, 1996), there are “large gaps in the body of knowledge” (Alavi and Leidner, 2001) in the area of knowledge re-use and knowledge transfer (Nissen, 2002).

So far, decision makers in organizational systems often make their decisions based on individual mental models. This does not necessarily result in appropriate outcomes (e.g. Dane and Pratt, 2007). The problem is that decisions in organizational systems do not necessarily rely on individual decision makers but also on experts working in the specific domain providing a larger knowledge base (Skraba et al., 2003). Therefore it is essential to develop knowledge of internal and external environments (Bergman et al., 2004). In addition, Sterman (2001) underlines that “dynamic complexity, tacit knowledge factors, feedback effects over time, and unstructuredness are responsible for many problems in business management”. On this account, we use the SD approach as a proper and well suited methodology.

Originally, SD is based on system theory and is able to comprehensively identify, analyze, and simulate complex causal structures of managerial systems for the “design of improved organizational form and guiding policy” (Forrester, 1969; Forrester, 1971). According to Morecroft et al. (1994), the application of SD models often results in revisions and adaptations of decision rules and learning effects in terms of future decision making. These enhancements are based on the integration of time delays, nonlinearities, and non-intuitive feedback loops (e.g. Sterman, 2000; Wolstenholme, 2003).

Although there are many papers in decision support literature that investigate dynamic effects, we barely find research referring to the SD approach in the context of knowledge-based decision support. Yim et al. (2004) present a SD approach investigating knowledge-based decision making with emphasis to strategic concerns. Even though this paper demonstrates a possible way to transform individual mental models into explicit knowledge, the authors do not show how to react appropriately to sudden changes in terms of short-term and long-term consequences. Additionally, the re-creation of knowledge for improving decision support is not considered.

Since the SD methodology strives for the goal of “qualitative description and exploration as well as quantitative simulation and analysis for the design of complex model structure and behavior” (Sterman, 2001), we apply this approach to investigate knowledge-based decision support.

2.2 Non-renewable resources

The discussion about the scarcity of non-renewable resources is a long-known and recurring topic. Already 80 years ago, Harold Hotelling referred to their rapid and unsustainable exploitation

(Hotelling, 1931). This view was quantified by Meadows et al. (1972) in the controversially discussed Club of Rome study “Limits to Growth” claiming the exhaustion of reserves of many non-renewable resources within the next few decades. Since then literature has discussed and contributed to this field from various perspectives. In order to structure theoretical findings and related work on different aspects of non-renewable resources, we subsequently distinguish the three domains *mining*, *market*, and *usage & recycling*.

First, the *mining* domain contains related work regarding how non-renewable resources are made available through exploration efforts and subsequent exploitation. Tilton (2002) defines non-renewable resources as “mineral resources” which are finite since the world is finite. Hence, if demand persists, depletion will be ineluctably at some point in the future (in literature this position is known as “fixed stock paradigm” (Tilton, 1996)). This point was first simply calculated by dividing the current reserves by the annual demand for production (reserves-to-production ratio). But following this logic, many resources (e.g. tin) would already have been exhausted (Meadows et al., 1972). Although the world’s finiteness cannot be denied, due to the huge abundance of non-renewable resources in the earth’s crust, geological availability is not a critical issue (Tilton, 2009; European Commission, 2010). In contrast to the widespread apprehension of non-renewable resources’ depletion, there are arguments that mining can keep up with the future rising demands (Tilton, 2009).

Work of the second domain (the *market* perspective) examines how discrepancies between supply and demand are balanced through price adjustments. According to Tilton (2009), economic depletion is a more critical issue than physical depletion and would “occur gradually over time as the real prices of mineral commodities rise persistently”. So, scarcity of non-renewable resources is seen as an economic problem (a position known as “opportunity cost paradigm” (Tilton, 1996)). On the one hand, it is expected that the demand for most non-renewable resources will continue to increase in the future (European Commission, 2010). In addition, exploitation costs may rise and demand can be met by supply only with delays (According to Hartman and Mutmanský (2002) a new mine can only be exploited after 5 to 13 years and requires multi-million investments). Modeling future developments should also take into account lower ore quality of non-renewable resource deposits as the rate of exploitable resources in a mine’s ores decreases (Krautkraemer, 1998). On the other hand, new technological findings and recycling might compensate these cost-increasing effects. In fact, over the last decades many metals have actually declined in price (Svedberg and Tilton, 2006; Radetzki, 2008). Nevertheless, it remains an open question to what extent the empirically observed quality decrease of ore grade of future explorations is offset (or even overcompensated as Tilton (2009) suggests) by technological advances driving down exploitation cost (van Vuuren et al., 1999).

The third domain deals with the *usage* of non-renewable resources to manufacture products and their *recycling* (if applicable) after use. Unlike many other substances, most non-renewable resources as metals will not be physically consumed. Instead, they can be used an infinite number of times. However, as of today many valuable non-renewable resources are lost due to dissipation and shortcomings of recycling. Reasons include non-economic recycling costs, lacking recycling facilities or dissipative usage, like in the case of zinc as corrosion protection (Plachy, 2004). The question to what extent non-renewable resources can be recycled depends on the field of application. For instance, indium is difficult to recycle due to its low concentration in typical indium containing products like liquid crystal displays (LCDs) (Tolcin, 2009). In contrast, the vast majority of copper, i.e. contained in cables or pipes, can be recycled more easily (Goonan, 2010). Thus, for each product and each application, there is a ratio of factual recycling, a ratio of technically possible recycling and a ratio of economically feasible recycling. In addition, other approaches like re-use and remanufacturing can improve the usage of non-renewable resources, as for instance LCD are fit for re-use or remanufacturing in many cases.

3 System Dynamics Model

Subsequently, we present a simulation model that formalizes knowledge of structure and behavior of non-renewable resources' use. Thereby, it takes the perspective of a production company that needs a non-renewable resource to manufacture one or more of its products. The model separates knowledge about system structure and behavior from the information required to instantiate the system. This shall help in reevaluating the situation once new information becomes available. Scenarios can be built to capture knowledge about possible fundamental price ranges (i.e. excluding speculation effects) as well as demand and supply developments depending on defined assumptions. While admittedly the assumptions themselves represent simplifications of the real-world, a coherent company-wide set of assumptions defined by experts is expected to outperform the various individual interpretations.

Our model draws from several approaches. The most important elements are: Opportunity cost paradigm (future demand estimations fail to incorporate future demand changes due to the price elasticity of demand), two kinds of resource sources, namely primary (mining) and secondary (recycling), and the pricing strategy of producers (mining and recycling companies will adjust their profit margin based on factors as e.g. the supply-demand ratio).

While there are many effects worth considering, we focus on a set of accepted and crucial elements to keep the model comprehensible. Most simplifying assumptions made can be subsequently relaxed through small changes to the model (e.g. adding new feedback loops to incorporate other price-influencing factors) or the use of more intricate mathematical distributions. A wide range of distributions is supported by the simulation software we used (Vensim® DSS 5.9e).

3.1 Model structure

Figure 1 shows the simulation model. The general model logic draws from findings of van Vuuren et al. (1999) with two additions. At first, a company perspective is adopted with a focus on decision support for the use of non-renewable resources. Second, the possibility to dynamically incorporate information changes is added. By means of scenarios knowledge can be communicated within a company. To point out how we use SD for these objectives, we will delineate the core concepts (represented by *italicized* words) below.

The stock *Reserves* represents the current amount of reserves made available by mining companies for the production industry. Based on empirical evidence from historical data (European Commission, 2010) reserves are expected to increase in future due to new findings. This increase of non-renewable resources is indicated by the inflow *material exploration*.

On the other hand, reserves will decrease – modeled as flow variable *material to mine* – based on those resources required by the production industry in order to satisfy the demand. The *demand* is based on the variable *predicted demand* as of now via a Gompertz function (Boudreau et al., 2009), but also dynamically adjusted to price changes. The stock *Supply* contains the total amount of non-renewable resources available to the production process. It is reduced by the flow variable *material usage*, i.e. resources used in the production process (represented by the stock *Production*). At this stage resources are processed into products for consumers. The rate of material wasted in the production process step is calculated by means of the constant *average ratio of new scrap during production*. In this model, we assume that the total amount of new scrap material can be recovered and thus reintegrated into the production lifecycle (represented by the flow variable *new scrap*). The other part of the material will be used for production. The amount of sold products is modeled by the flow variable *consumption*.

The stock *Usage* represents the potentially long-standing utilization of non-renewable resources during the use of products by consumers. The average usage duration is determined as the constant *average period for usage*. After the expected product lifetime (represented by the flow variable *termination*), in

the stock *Decommissioning* the dumped products are classified according to their recyclability, represented by the constant *waste ratio*. If the dumped products are not recyclable (i.e. waste ratio = 1), the products will be totally dissipated (represented by the flow variable *dissipation*). In contrast, if the products are (partly) recyclable (i.e. $0 \leq \text{waste ratio} < 1$) they will be classified as *recyclable material*. This kind of material is collected in the stock *Recycling*. If the *average costs per recycled ton* are higher than the price (both variables are illustrated as shadow variables in angle brackets) for newly mined material, no material will be recycled since it is more profitable to purchase newly mined non-renewable resources. Otherwise, if the costs for recycling are lower than the price, recycling will become economically attractive and material will actually be recycled. In this case, a certain fraction (represented by the constant *recycling waste ratio*) of the recyclable material cannot be recovered during the recycling process which is visualized by the flow variable *recycling waste*. The rest of the non-renewable resource flows back as *recycled material* into supply considering the *average period for recycling*, i.e. the delay caused by the recycling process itself.

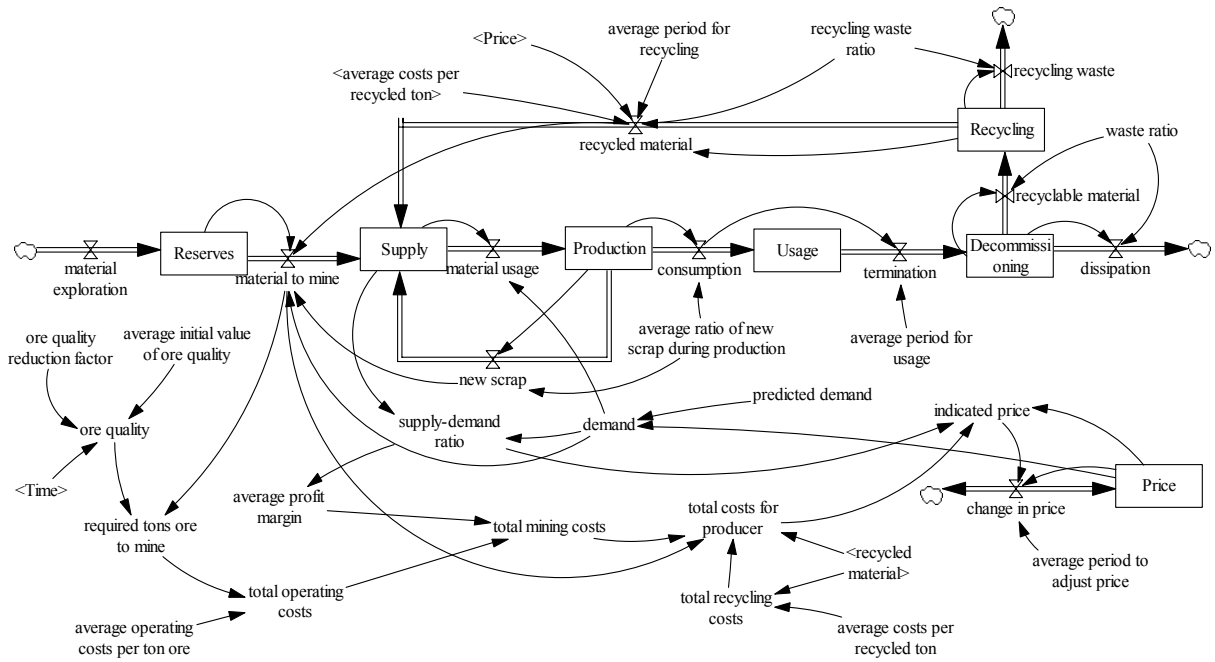


Figure 1. Simulation model

In order to investigate the consequences of discrepancies in supply and demand, we integrate the stock *Price* representing the fundamental price of the non-renewable resource. Considering the delay *average period to adjust price*, this stock will be changed (represented by the flow variable *change in price*) based on the difference between price and indicated price. The latter represents the target price that will be reached with the defined delay. It is calculated as follows:

$$\text{indicated price} = \text{MAX} \left(\frac{\text{Price}}{\text{supply} - \text{demand ratio}}, \text{total costs for producer} \right) \quad (1)$$

Here, the *supply-demand ratio* calculates the proportion of supply and demand. If supply is lower than demand, the indicated price will increase. Otherwise, the indicated price will decrease. We assume as minimum for the indicated price the *total costs for producer* per ton of the non-renewable resource in order to guarantee a long-term cost-effective exploitation for mining companies. These total costs are defined as the weighted average of the *total recycling costs* and the *total mining costs*. The first results from the multiplication of the recycled material by the average costs per recycled ton, whereas the second is calculated by the *average profit margin* (modeled as graphical function depending on supply-demand ratio) multiplied by the *total operating costs*. To determine these operating costs, we need to multiply the constant *average operating costs per ton ore* by the *required tons ore to mine*.

The latter variable is the amount of ore needed to gain the required tons of the non-renewable resource. Since the quality of deposits tends to decrease because better mines are exploited first, we need to incorporate the *ore quality*. This variable stands for the concentration of a non-renewable resource in the ore of a deposit, e.g. in parts per million (ppm) (Hartman and Mutmanský, 2002). The more ore is exhausted, the lower the concentration gets. For this reason, it becomes more intricate and expensive to extract the non-renewable resource. Our model applies an exponential decay function to calculate the ore quality which depends on the constant *average initial value of ore quality*, the temporal factor *Time*, and the *ore quality reduction factor*. This ore quality reduction factor determines the slope of the ore quality change: the lower the factor, the faster the ore quality decreases.

3.2 Model behavior

The model behavior arises from its structure, integrating dynamic complexity through overlapping short-term and long-term effects. In order to improve the mental model of a decision maker it is necessary to examine the essential feedback loops. The fundamental modes of feedback loops are exponential growth, goal seeking, oscillation, and interactions of these (for further detail, see Sterman, 2000 and Wolstenholme, 2003). Since the model contains various feedback loops we concentrate on the pivotal ones which integrate the key factors of the research question (i.e. demand, supply, and price). On this account, we take an isolated perspective on both the cause and the effect variable (i.e. a *ceteris paribus* consideration).

First, we examine two essential feedback loops for the demand and its impact on costs and mining: the *demand-profit margin loop* and the *demand-material loop*. For the former loop we assume the lower the supply-demand-ratio, the higher the average profit margin is that mining companies can claim. It raises the total costs the production company has to pay. This results in an increase of the indicated price and, in turn, reduces the demand at last. Therefore, in the long run the demand-profit margin loop is characterized by a goal seeking behavior. In the latter loop a higher demand leads to a higher amount of material to mine. Due to the decreasing ore quality over time, more tons of ore are required to satisfy the demand. This effect increases the total operating costs and, again, the total costs for the production company. Through the increase of the price, the demand will reduce. This is a goal seeking loop, too.

The main feedback loops for supply are named *supply-recycling loop* and *supply-price loop*. The former determines the transition of a non-renewable resource from supply across production, usage, decommissioning and recycling back to supply. The assumed s-shaped growth of this loop results from an exponential growth which then gradually slows until the state of the system reaches the equilibrium level, i.e. the demand in this case. This behavior is based on an overlap of the two fundamental modes exponential growth and goal seeking in the underlying model structure. The latter loop examines the impact of supply on the price for the non-renewable resource. Through a raise in the supply the supply-demand ratio increases. This leads to reductions of the indicated price and, in turn, the price. A lower price drives demand which finally increases supply. Hence, the behavior of the loop is exponential growth.

Finally, we investigate the main feedback effects in terms of price. Considering the *price-recycling loop*, an increase of the price will also lead to a raise in the amount of recycled material (conditionally to the technical possibility of recycling) if the costs for recycling fall below the price for mining new non-renewable resources. The recycled material will increase the supply, thus reducing the indicated price and the price at last. Therefore, this loop demonstrates a goal seeking behavior.

Since model structure and model behavior are determined, in the following section we exemplarily apply the model for the non-renewable resource indium. Based on comprehensible assumptions and facts from literature we establish three scenarios in order to demonstrate both the model's applicability in principle and the effects on the key variables demand, supply, and price. In a real-world application, the assumptions and facts would stem from company-internal experts that use this approach to make their knowledge explicit in order to foster a company-wide coherent view for decision making.

4 Exemplary Application and Scenario Analysis

Since the mid of 1980s – when indium started to gain economic relevance – both annual consumption and price have multiplied tenfold (USGS, 2007). The upward trend is expected to continue. The European Commission (2010) assumes indium demand to triple until 2030 due to its importance for the production of LCDs, touch panels, and thin film solar cells.

But while the occurrence of former demand and supply predictions would have resulted in faster-growing depletion of indium and higher market prices, despite growing demand indium prices have declined compared to their high four years ago (USGS, 2010). While the observed relaxation has mainly been attributed to new explorations, this is not the only factor playing a pivotal role:

- *New explorations.* In 2007, China corrected its indium reserves from 280 to 8,000 tons (USGS, 2007; USGS, 2008).
- *Delayed reactions.* In case of scarcity of indium, other mines could – with some delay – take over production since indium is produced as a by-product of other non-renewable resources as lead, zinc, copper, tin and silver (Mikolajczak, 2009).
- *Recycling.* While indium “lost” during the production process is already reclaimed, recycling from end products as LCDs is currently not economically feasible (Mikolajczak, 2009).
- *Substitution.* For most applications of indium, substitution candidates have been found. But their commercial feasibility is not always given – and if so, a delay of some years is involved (USGS, 2010).

These factors and their interconnectedness increase the risk for decision makers to misjudge the situation due to partial or improper knowledge. To determine the probable range of future demand, supply and price developments (excluding speculation effects), we subsequently define and simulate three scenarios – a base case, a pessimistic case and an optimistic case – covering a wide range of assumptions currently found in real-world discussions.

4.1 Scenario description

The input parameters for the scenarios originate from literature as geological studies, reports of mining engineering companies, and long-term socio-economic forecasts. Knowledge about the solution space can be communicated to decision makers by means of different scenarios. Since the model’s behavior is set to adjust supply to demand (conditionally to sufficient reserves or recycling capacity), we concentrate on five variables that either drive demand or influence the supply capacity. The former can be influenced directly (through different assumptions for the *predicted demand* in 2030) or indirectly (since a change in *ore quality* drives production cost as lower boundary for the price which in turn alters demand due to its elasticity). The latter can be divided into a primary supply capacity (depending on known and newly discovered reserves) and a secondary supply capacity (depending on feasibility of recycling). The supply capacity is characterized through the three variables *initial value of reserves*, *material exploration* and *waste ratio*. Table 1 gives an overview of both variables and their respective scenario instantiations.

While the base case has been designed with values currently assumed to have the highest probability, both other cases provide lower and upper boundaries in order to take into account potential pessimistic and optimistic developments. In a company, these scenarios and values would need to be defined by experts, e.g. from the strategy department.

The *predicted demand* forecast of 2,000 tons per annum in 2030 is seen as the most probable value and is based on an extensive study incorporating multiple forecasts for key technologies (Angerer et al., 2009). In an pessimistic case, new technologies could lead to an increased demand of up to 5,000 tons, for instance in case of further growing demand for thin film solar cells. On the other hand,

more efficient technologies could lower the demand of newly mined indium to about 500 tons per year (Mikolajczak, 2009).

Variable	Description	Base case	Pessimistic case	Optimistic case
<i>Predicted demand</i>	Expected demand of indium in 2030 [in tons per year]	2,000	5,000	500
<i>material exploration</i>	Expected explorations of new indium deposits [in tons per year]	1,000	500	1,000
<i>initial value of reserves</i>	Expected initial reserves of indium [in tons]	11,000	7,000	64,000
<i>waste ratio</i>	Share of not recyclable indium in products [in %]	90%	100%	60%
	Time to reach technical feasibility of recycling [in years]	10	20	5
<i>ore quality</i>	Average quality change of indium ore concentrates during the simulation [in ppm] → [in ppm]	100 → 80	100 → 50	100 → 140

Table 1. Input parameters for the scenarios

The amount of new indium deposits – represented by the *material exploration* variable – is subject to controversial discussions. Basically, indium is about as frequent as silver and by these means not very rare (Jorgenson and George, 2005; USGS, 2010). Empirical evidence shows that the so-called static life time of reserve base for indium was in 2007 higher than in 1989 (European Commission, 2010). New explorations can explain this phenomenon. Hence, we assume a yearly material exploration rate of 1,000 tons for both base and optimistic case but a lower rate of 500 tons for the pessimistic case.

Furthermore, not only the increase of reserves but also the *initial value of reserves* could affect the system's behavior. While today there are known reserves of 11,000 tons (USGS, 2008), Mikolajczak (2009) claims that much more indium can be found. For the optimistic case we follow his logic and assume reserves of 64,000 tons. In the pessimistic case we fear that expert estimations are overly optimistic. Hence, the current reserves are reduced to 7,000 tons.

Currently, up to 70% of indium is wasted during the manufacturing process (new scrap) but can be regained within 30 days (Mikolajczak, 2009). However, the indium contained in end products is not recycled so far. For the pessimistic case we assume this situation to remain unchanged for the next 20 years (i.e. the *waste ratio* remains at 100%). In the base case recycling becomes technically feasible for up to 10% of indium contained in end products after ten years. Optimistically, the recycling ratio can increase to 40% within the next five years. The latter two cases only represent assumptions about technical feasibility – economical feasibility is inherent to the models behavior due to its price dependency.

The *ore quality* of indium deposits is a key factor for cost and price developments. Since indium is a by-product of ores containing other metals, it is difficult to apply the idea to presume a general ore quality decline as described by van Vuuren et al. (1999). Rather, indium ore quality depends on the underlying ore concentrate. Currently, mining is economically feasible for concentrates containing as little as 100 ppm of indium (Mikolajczak, 2009). In the base case this is assumed to decrease to 80 ppm. On the other hand, there are mines like the recently closed Toyoha mine in Japan with an indium concentration of about 140 ppm (Jorgenson and George, 2005). Hence, this value is set as an upper boundary in the optimistic case arguing that higher and relatively new exploration efforts will result in higher concentrations to be found. On the other hand, high quality deposits could be exhausted sooner than expected leading to a lower ore quality of 50 ppm – the average content of indium in zinc deposits (USGS, 2010).

In summary, the five variables constituting the three scenarios represent a wide range of facts and plausible assumptions thereby allowing reasonable simulations.

4.2 Simulation results

Based on the input parameters described above, we ran simulations for each of the three scenarios. In the base case, the price steadily rises from \$500 per kg indium in 2010 to \$749 in 2030 following an s-shaped growth. This equals a yearly average price-increase-rate of about 2%. While one could expect higher prices due to increasing demand, this is counteracted by a rather moderate increase of mining costs and the exploration of new resources. On the other hand, new substitution technologies and favorable exploration of new deposits could reduce the demand and increase ore quality. This has been simulated in the optimistic case. Here, the price gradually reduces to \$100 per kg, converging at mining costs that decrease due to higher grade indium deposits. Lastly, there is the possibility of a combination of multiple unfavorable developments. Strongly increasing demand combined with a serious reduction of ore quality can lead to an extreme price increase. In the pessimistic case, the price triples to more than \$1,500 per kg, equaling more than ten times the price of 2000.

As a rather surprising result, the new scrap rate turned out to be an important element for the price development. Since up to 70% of indium used in LCD production is first lost and then recycled (Mikolajczak, 2009), this implies that large amounts of indium are circulating in production facilities. Here, decreases in the new scrap rate result in a price increase by a factor of two, making the new scrap rate on major price determinant. This effect can be explained through the stabilizing effects of new scrap on supply. Additional simulations also demonstrated that recycling can provide an upper boundary for indium prices – although costs for recycling are too high to provide an economically feasible alternative in the presented cases.

Altogether, besides a number of rather expectable findings, our simulation produced some surprising results, demonstrating the ability of SD to capture complex knowledge. Large amounts of previously incoherent information could be combined in a meaningful way, contributing to the re-creation of knowledge from plausible assumptions and formerly disconnected facts. In particular, scenarios help to communicate knowledge regarding possible variants of future developments of demand, supply and price.

5 Limitations and Outlook

The primary objective of this paper was to develop a SD model for decision support in order to contribute to knowledge re-use and re-creation for better organizational performance. In the context of the use of non-renewable resources we uncovered and examined short- and long-term consequences on demand, supply, and price. The resulting model can be seen as an explicitly formalized mental model of one or several experts. We used the case of indium to show how externalized and combined real-world information used in scenarios can enable a company to communicate a coherent and comprehensive view for strategic decisions.

Admittedly, the presented research is beset with shortcomings and limitations that will be addressed in future endeavors: First, a company-wide consistent view does neither necessarily improve decision quality nor ensures a better understanding of a system's structure and behavior. Second, the level of detail of the presented model could be questioned. To gain a more holistic view in terms of recycling, the concepts of re-use and remanufacturing could be integrated as well. Third, while knowledge about fundamental market structures and dynamics is considered, other factors a decision maker needs to keep in mind are not modeled. For example, the price for a non-renewable resource not only results from fundamental economic developments but also from factors as speculation. While there are SD-based approaches to capture such factors as well (Witte and Suchan, 2010) the required assumptions to predict the actual price would stem from "gazing into crystal balls" and prevent decision makers from focusing on fundamental effects. Fourth, even though we based our model on findings from literature

to approximate system behavior, an empirical validation based on past data is missing. Fifth, an application of this model in a corporate environment would help to identify further improvements. Therefore, it would be insightful and strengthen evaluation to conduct additional studies.

Nevertheless, the proposed model demonstrates how SD models can be used to capture implicit knowledge of a system's structure and behavior thereby improving knowledge-based decision support. A set of expert beliefs (formalized as assumptions) and facts can be shared and aligned company-wide in order to contribute to a coherent knowledge base. This is especially important in fields that are controversially discussed and require a continually re-use and re-creation of knowledge as e.g. the demand, supply, and price developments of non-renewable resources.

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