The preservation of material flows in recycling processes for further usage

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Abstract Recycling processes generate many material flows that are of equal quality as primary resources gained from mining operations. Often they save resources like material and energy. This paper discusses the information needed to evaluate the potential of materials flows in recycling processes to preserve primary resources. Main issue to look at are the uncertainties connected to recycling processes and the dissipative losses during the life cycle of products. Neural networks might be a solution to cope with vague data and high data ranges in recycling processes. In this paper we are presenting an approach how neural networks can support our attempt to handle the uncertainties connected to material flows.

1 Introduction

After processing end-of-life products in a recycling plant material flows of various qualities are generated. To save primary resources it is essential to keep as much material flows in the recycling loop as possible. But the further use of recycled material flows into high valuable materials is only possible through maintaining specific requirements of these secondary resources. Unfortunately, the material properties are associated with high uncertainty in recycling streams. By thoroughly and broadly identifying material properties the potential for further use of secondary resources can be assessed. A combination of the methodologies of Life Cycle Assessment, Material Flow Assessment, and Material Characterisation are quite useful here to establish the suitability of certain secondary material flows for further applications. The evidence of high uncertainties related to the properties of secondary material streams is cumbersome for the development of reliable models aimed at the prediction of waste material flows and their applications or potential for recovery. Dissipative losses of metals into other material streams, especially other metal cycles, sometimes substantially changes the properties of the receiving material stream. Copper in steel is only one example for this kind of quality problem. To assess the implications of this issue on the recyclability and sustainability of certain material flows, there is further research needed. Currently we only vaguely know the dissipative losses of metals in recycling operations. Material flow analysis with a focus on dissipation helps to shed some more light on this issue.

2 Material flows in recycling processes

2.1 Heterogenity of material flows and uncertainties

Materials treated in recycling processes have in common that they are no longer in use for their original purpose and have to be treated. Often they vary in their composition but after treatment we can identify material flows that are valuable resources for new and other applications. Nevertheless the known and unknown uncertainties become important parameters to consider within recycling processes. These uncertainties can have many sources. The uncertainty by itself has to be addressed at three places: the input side, the processing side and the output side. The variation of parameters is not always known and coincidental. For example there is data for which no value is available, data for which an inappropriate value is available, and data for which more than one value is available [1]. These are also called data defects and are discussed further in this paper. Due to the fact that residues always vary in their composition and material flow only data ranges can be used as input parameter. These values may fluctuate around a threshold with deviations of maximum and minimum uncertainties as depicted in figure 1. Normally we expect an exact data in our calculation or measurement. Figure 1 shows an example of the mass content of a specific material flow. The measured data (R) may be below, above or near a defined threshold. Potential uncertainties can lower (R-U) or raise (R+U) the data. Therefore, the handling of such data becomes difficult.

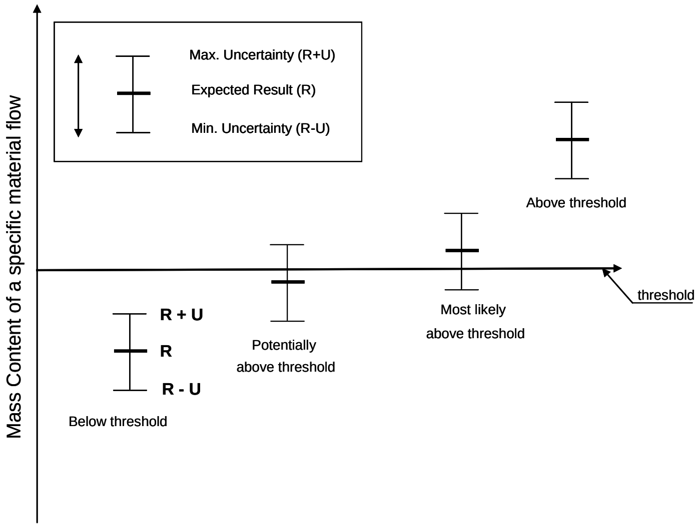

Figure 1: Variations of uncertainties around a threshold

Uncertainties play an evident role during the assessment of a recycling process or to support a decision based on environmental impacts of processes. Therefore, uncertainties in the process have to be identified and considered as a fact in recycling processes. Modelling recycling processes and the assessment of uncertainty are firmly connected; otherwise the model provides a lack of reliability due to parameter uncertainties. The known and unknown uncertainties of the process become important parameters to consider. Only data ranges can be used as input parameter due to the fact that waste flows always vary in their composition [2].

2.2 Methods to assess material flows

2.2.1 Life Cycle Assessment (LCA)

Life Cycle Assessment (LCA), which is used to assess the environmental impacts of products from cradle to grave, is increasingly being applied to the evaluation of waste management strategies. It should be noted, however, that there is a fundamental difference between the life cycle boundaries of products and wastes. The life cycle of a product starts with the extraction of raw materials (through activities such as mining, logging, etc.) and ends with the final disposal of a product [3]. The life cycle of waste on the other hand can be divided into two ways: Life cycles of secondary resources are often identified as open loop processes (conversion of material from one product into a new application) compared to closed loop processes (conversion of material into the same application).

Since 1992 the Society of Environmental Toxicology and Chemistry (SETAC) is organizing workshops focused exclusively on uncertainties in Life Cycle Assessments (LCA) [4]. Modelling recycling processes and the assessment of uncertainty are firmly connected; otherwise the model provides a lack of reliability due to parameter uncertainties. An interest on the credibility of process modelling due to the performed decisions based on the LCA is evident [5].

According to Finnveden [6] the interest in LCA grew rapidly during the 1990s, also when the first scientific publication emerged [7]. Since then a strong development and harmonization has occurred resulting in an international standard [8]. Since there are still open questions while performing LCAs there are several international initiatives to provide recommendations, including the Life Cycle Initiative of the United Nations Environment Program (UNEP) [9] and the Society of Environmental Toxicological and Chemistry, the European Platform for LCA of the European Commission [10], and the emerging International Reference Life Cycle Data System.

The management of product life cycle includes the best knowledge of processes and their system boundaries. All recycling processes have in common that their input material has already had a complete life cycle; therefore it is more difficult to find exact input data for the LCA of the recycling process. Attention has to be paid to uncertainties in performing LCAs in recycling processes. These days life cycles of secondary resources are no longer within the system boundary from “cradle to grave”; instead we have to look at a life cycle from “cradle to cradle” [11]. Resource flows are important for LCAs since they try to consider all input and output flows. The following chapter gives an overview on the Material Flow Assessment.

2.2.2 Material Flow Assessment (MFA)

Material Flow Analysis (MFA) is a systematic assessment of the flows and stocks of materials within a system defined in space and time [12]. It connects the sources, the pathways, and the final sinks of a material. An MFA delivers a complete and consistent set of information about all stocks and flows of a particular material within a system. The MFA can be regarded as a method to establish the inventory for an LCA.

Material Flow Assessment can be easily applied to recycling processes because it takes into account all material flows entering and leaving the recycling process (system boarder). Since the input in recycling processes is often a mixture of various material streams the exact composition is never known. There is often a lack of information due to unknown parameters in material composition or processing steps [13]. Due to the high potential of recycling processes contributing to a sustainable management of resources (e.g. energy savings and material efficiency) it is necessary to assess the material flows with the regard to their environmental impact [14], [15]. Material flows in recycling operations have in common that they often consist of material impurities since the effort to completely separate materials is often not feasible. Therefore, the exact composition of output flows is variable. As a matter of fact this becomes even more evident when we consider dissipative losses in recycling processes.

2.3 Dissipative losses and material characterisation

Dissipation of materials is significant obstacle to efficient recycling and it is our belief that its needs to be considered in material flow analyses for a full evaluation of the performance of the processes. The consideration of dissipation implies the necessity of detailed data on material composition, which usually goes beyond elementary analysis and takes into account the chemical composition of the materials involved and possibly their structural characteristics (grain size etc). These data requirements can be part of a detailed material characterisation scheme, which needs to be implemented when modelling, evaluating and controlling recycling operations.

We use a rather broad definition of the term dissipative losses, including all losses to the environment and other material streams which are resulting in concentrations in the target medium below a level where recovery is physically or economically feasible. Dissipative losses can occur intentionally or unintentionally. Famous examples are the wear and tear from overhead railway traction lines made from copper, abrasion of brake pads, dissipative use of metals in pesticides and pigments, or losses of copper to the steel cycle in recycling operations.

Here we want to focus on the dissipation of metals into other metal cycles and metallurgical byproducts (e.g. slags), as this poses several challenges for recycling: a) the dissipated metal is lost, b) the receiving metal cycle is contaminated and c) when the byproducts are exposed to weathering, toxic emissions might occur. The loss of metals due to dissipation into other material cycles is a serious issue for critical metals, i.e. metals which have a high economic importance and which suffer from higher than normal supply risks. Copper is such an example, as it can almost not be substituted, is already in high demand, and the demand will likely further rise due to an expected production increase in electronic products, power generators, renewable energy technologies, electric vehicles, electricity infrastructures and so on [16]. On the other hand, the recycling efficiency rate of copper (copper recovered in recycling/copper available for recycling in obsolete products) in 1999 was only around 67%, with approximately 33% losses [17]. At least 17% losses occur into other material streams, most of which can be labeled as dissipative. Around 6% of the copper available for recycling ends up highly dissipated in other metal loops, mainly steel and aluminum [18]. The copper losses into steel have a negative impact on the steel quality and should be avoided as much as possible. In future, this problem might become worse, with an increase in small size WEEE (losses to waste dumps and incinerator ashes), an increase in electronics in vehicles (loss to the steel cycle) and an increase of non-electrical industrial waste (losses to other metal loops, including steel) [18].

When metal flow systems (e.g. reycling operations) are to be evaluated, dissipation thus needs to be taken into account. A focus on mass flows alone does not suffice to capture the characteristic of metal flows, since the quality of these flows is crucial to the further processing and use options for these metals. We need to adress two different questions regarding dissipative losses of metals: i) where do the metals, especially the critical metals, end up and ii) in what concentration. In order to do so, we need detailed information on the metal contents of material flows (inputs and outputs). For the case of recycling processes, we are looking for answers to the question whether the process dissipates a metal or whether it concentrates a metal. Recycling operations usually aim at concentration, but in many cases the concentration of one metal is accompanied by the dissipation of another. Steel recycling is such an example: while the copper fraction in obsolete steel products is usually highly concentrated (e.g. in small electrical motors embedded in the steel scrap), after recycling the copper is finely dissipated within the produced steel. While the concentration of iron increases during the operation, the concentration of copper decreases. This is also true for other metals in the steel scrap, only that their dissipation is not as harmful to the steel cycle (with the exception of tin). In general, the effectiveness of recycling operations should be based on an analysis of all metals, at least the critical ones, present in the scrap. When the concentration and dissipation of all these metals is evaluated, a complete picture of the quality of the recycling process emerges. A good measure for overall dissipation or concentration of metals in the process is the specific statistical entropy of the metals in the mixtures (entropy of

mixing). These can be calculated for all relevant metals and compared between input flows and output flows (for the methodology see [19]). First test calculations for specific recycling operations have been performed [20], [21]. The results indicate, that although the processes analysed generally concentrate the metals present in the inputs, some metals are rather dissipated. For a recycling process of zinc rich electric arc furnace dust, for example, 9 out of 13 metals are concentrated to varying degrees, with high concentration factors for iron, calcium, magnesium and zinc. The overall concentration is apparent in the fact that the total entropy of mixing is decreased by 33% [20]. Still, 4 metals are dissipated: manganese, molybdenum, nickel and titan. Since at least molybdenum and manganese are viewed as critical metals [22], [16] there seems to be an incentive to increase the effectiveness of this particular process. Without having analysed more processes in detail, a comparison of the absolute effectiveness of the process seems difficult, but 33% decrease in mixing does seem to leave some room for improvement.
The analysis presented above can in principle be applied to all kinds of metal recycling operation. With a few alterations, it might also be applicable to other material flows (paper, rubber, minerals), if there is a need to address dissipation. For metal recycling operations the analysis of the "mixedness" of input, output and intermediary flows generates valuable insights into the effectiveness of the operations and helps identify hot spots for optimisation. The increase in overall metal concentrations can also serve as the base line for efficiency comparisons. The efficiency would then be the ratio of concentration achieved versus efforts spent, where "efforts" could be evaluated by energy demand, environmental burdens or thermodynamically assessed resource consumption [23], [24].

3 Assessing the recyclability and sustainability of recycled material flows

Due to diverse origins of recycling materials information on recycling processes is not fully available for all process steps and materials. For examples metal analyses of material flows over a defined time frame will be in a specific data range and therefore only mean values are suitable for calculation and modeling. In this case we are applying a metamodel technique. A metamodel describes the structure of a model and uses mainly the information generated from processing steps for example. This results in an abstract combination of the elements of the model and its linkages. Therefore, this technique allows developing the model. In our approach the tools to build this model are common LCA software to define the mathematical connections between processing steps and their flows.

A metamodel describes a theoretical performance of the model on a high level of abstraction to support the construction of a prediction model for real processes. Complex processes are divided into smaller modules with main effects on the process (modular construction system). Since the functional correlation between modules is often unknown "black-box" models are in use. These "black-box" models have direct or indirect influence on the process step through their input parameters and are therefore important for all following process steps.

A knowledge-based decision support system (see Figure 2) uses mainly the information generated by processing steps resulting in an abstract combination of the elements of the model and its linkages. Hence, this technique allows developing a model. Instead of specific data it processes the information of a process (e.g. dismantling of waste products into components of different shapes and compositions). Collecting information on the "flow in" can be made accessible through existing databases like ecoinvent (ecoinvent Centre, Switzerland), international databases for LCA (ELCD/ILCD), recycling stock exchanges or own data pools. Calculating input data are performed with program interfaces on statistical basis. Finally, information on output data (flow out) can be generated through a developed knowledge-based decision support system. The accuracy of the model relies on the data availability and its quality. Therefore, it is necessary to have a well operated network.

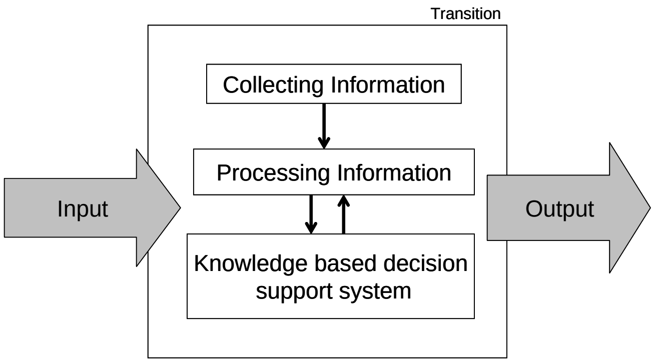

Figure 2: Metamodel architecture based on knowledged-based decision support system

4 Network adjusting by using petri nets and neural networks

To meet the challenge to cope with uncertainties in this case we suggest a hybrid system which combines Petri nets and neural networks with a case based reasoning approach. We use the advantages of Petri nets in order to overcome the neural network deficiencies concerning their original design and definition of their initial weighs. Our solution solves uncertainty problems of process data defects using neural networks and case based systems together. Recovered similar cases have allowed the readjusting the network solutions, as well as the correction data. Another advantage would be to propose several solutions to experts.

Neural networks are used in different fields. Classification is one of problems where they are commonly and very often used. The Back-propagation algorithm is one of the most widely-used for training feed-forward neural networks because of its simplicity and capability to extract useful information from the examples and implicitly store it in their weighing connections [25], [26]. This algorithm has some limitations in its practical use that are generally approached and accepted by researchers. Some of these limitations are that its convergence toward a state of minimum error can be extremely slow, mainly if the size of the network is not big enough regarding the size of the problem. Next, it can standby in local minima before finishing the learning of all the examples, and finally, it is almost impossible to select the design of the network before hand [26]. Due to its complexity and slow process, a lot of software is developed to help the designers of these networks in the design and implementation of Multilayer Perceptrons (MLP). New training algorithms are implemented to achieve results similar to the traditional ones, in a very short time. Petri Nets are alternative tools for the study of non-deterministic, concurrent, parallel, asynchronous, distributed or stochastic systems. They can model systems in an easy and natural way. Furthermore, the Petri Nets approach can be easily combined with other techniques and theories such as object-oriented programming, fuzzy theory, neural networks, etc. These modified Petri Nets are widely used in computing, manufacturing, robotic, knowledge based systems, process control, as well as in other kinds of engineering applications [27]. Since Petri Nets offer advantages to model systems and can interact with other techniques easily, it would be advantageous to model neural networks starting from Petri Net models, which allow not only the design adjustment but also the initialization of the neural network weights. Following the algorithm proposed by Xiaoou Li and Wen Yu in [27], we can model a neural network starting from a Petri net with the application of weighty production rules in the algorithm. The learning algorithm of the neural networks obtained is the same as the backpropagation of multilayer neural networks. The main idea is that all layer weights can be updated through the backpropagation algorithm if certainty factors of all sink places are given [26]. A complex neuronal network can be divided into several sub-networks starting from the modular design of an original Petri Net. The designed sub-networks will correspond to the real application of sub-processes.

5 Discussion and Outlook

The preservation of material flows in recycling processes for further usage is strongly connected to the material characterisation. With the definition of material properties and material qualities the further usage of material flows can be enhanced. Materials can be preserved through directing material flows into most suitable recycling processes. According to high uncertainties in recycling processes and recycled materials a solution for a proper information system has to be implemented. Our attempt for the varying data is a hybrid system which combines Petri nets and neural networks with a case based reasoning approach. More research has to be done to present a reliable model.

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