Official URL: https://doi.org/10.1007/978-0-85729-320-6_33

DISASSEMBLY PROCESS PLANNING USING BAYESIAN NETWORKS

Godichaud M.[a] , Pérès F. [a] and Tchangani A. [a]

[a] *Laboratoire Génie de Production, Ecole Nationale d'Ingénieur de Tarbes*
47, Avenue d'Azereix – BP 1629 – Tarbes Cedex - France
matthieu.godichaud@enit.fr, francois.peres@enit.fr, ayeley.tchangani@enit.fr

The management of end-of-life systems becomes more and more important due to the awareness of their environmental impact. In this context, the disassembly process requires more attention with the ultimate goal to make profit. In this paper, we propose a new approach to determine optimal disassembly plan of an end-of-life system by using bayesian network. To take advantage of some existing approaches that use Petri Net to model such process, a Petri Net model is first established and then translated to Bayesian Network in order to take into account inevitable uncertainties associated to such process.

Key Words: Disassembly, modelling, Bayesian networks, uncertainties.

1 INTRODUCTION

The end-of-life phase of systems life-cycle has become more and more important since several years. This is firstly due to the reinforcement of the government legislation with regard to environmental protection that forces the system manufacturers to take care of the disposal in an environmental conscious way. Different activities are required to achieve this goal. They allow bringing back the components of the end-of-life system to conditions that enable their reintroduction in the life-cycle of other systems. The principal activities are material recycling, remanufacturing or reusing. In this paper, we classify these activities in two generic classes:

– material recycling which consists in material recovery of the system elements;

– functional recycling which consists in functional recovery of the system elements.

These activities can generate profits for the actors of the end-of-life phase who manage the disassembly of the system. Today, the awareness of economic profit perspectives becomes one of the principal motivations for system manufacturers to set up and develop disassembly process.

The objective of the disassembly process is to generate parts and subassemblies that respect the specifications and conditions of the recovery activities (recycling, reuse, …) to which they are assigned to. The disassembly process includes sequences of separation actions that go from the whole end-of-life system to the valuable recycling products that the decision-maker has selected. Different separation actions are possible to obtain each product (destructive, non-destructive, shredding, sorting, …) and different recycling options can be in conflict in one disassembly strategy.

The definition of a disassembly strategy begins with an analysis phase. We decompose this phase in three main tasks:

– identification of the component and subassembly of the end-of-life system: the purpose here is to represent the product topology and mating relationships;

– identification of the recycling actors who can evaluate different components with recycling viewpoints;

– analysis of the separation actions and resources in order to determine the precedence constraints between separation actions.

In the next step, decision-maker has to determine the optimal solution according to some criteria. The solution must establish for each component the best recycling option, the disassembly level (i.e. for each subassembly, what is the best option between recover and disassembly?) and for each subassembly the best type of separation actions. For a system with an important size, these tasks appear to be complex since the number of solutions might be important.

Furthermore, decision-maker has to manage the uncertainty of the disassembly process. Indeed, this is an important characteristic of this process but there are only few works that deals with it in the disassembly literature. The main uncertainties in the disassembly process are related to the states of the systems and components as well as the demand for the recovery products. There are two approaches to cope with this problem: predictive or reactive. The first one consists in selecting one solution that integrates the uncertain parameters. They can be taken into account in the decision model by introducing probabilities on success of disassembly operations [16] or by specifying parameter values by intervals [7]. The second approach to take into account uncertainties consists in keeping alternative sequences in the disassembly process model in order to change the principal sequence if an operation fails [6] [10] [3].

The research issues we address in this work concern the modelling of the decision problem in disassembly planning with uncertainty. The remainder of the paper is organized as following: in the second section we present the necessary steps to modeling disassembly planning problem; in the third section we present our approach for solving such problem by using Bayesian network and in the last section we illustrate this approach on an example.

2 DISASSEMBLY PLANNING PROBLEM

2.1 Problem modelling framework

In this section, we present the different steps in modelling the disassembly planning problem that lead to an optimal disassembly sequences. In a determinist context, there are many works that address these problems in the literature (see for instance [2][7]). We present a way of linking these different approaches.

Generally, the modelling of the disassembly planning problem requires three main steps (see Figure 1). The first step concerns the structure modelling of the end-of-life system. The goal of these models is to represent the valuable parts and subassemblies and the connections between them. The input data can be generated from CAD (Computer Aided Design) systems as well as MRP (Material Requirement Planning) systems which facilitate the activity of identifying the components that can be reused. Several models are proposed in the literature ([1][9][12]).

The second step (denoted by Process models in Figure 1) of the disassembly planning problem concerns the modeling of the disassembly process. The obtained model represents the different operations that can be made on the system to obtain the valuable part and subassembly. After each disassembly operation, the state (or structure) of the end-of-life system is modified. If necessary, the process model integrates these intermediate structures. This is interesting when decision-maker wants to take into account the uncertainty of operation success. Indeed, if one operation fails, one has to manage the intermediate component generated previously. The problem is to generate all the sequences of disassembly operations that respect the precedence constraints identified in the structure model. The main difference between several sequences is due to the changes of tools and disassembly axis as well as varying accessibility of parts. The consequence is the variation of operation time and costs (see [7][15] for instance).

The third step (Decision models in Figure 1) concerns the search of the optimal sequence among those identified in the process model. The purpose is to jointly determine the disassembly level and sequence. The model must take into account the preferences of the different stakeholders involved in the end-of-life phase of the system. Classic approaches model the decision problem as a linear program and solve it by existing algorithms ([7][8]).

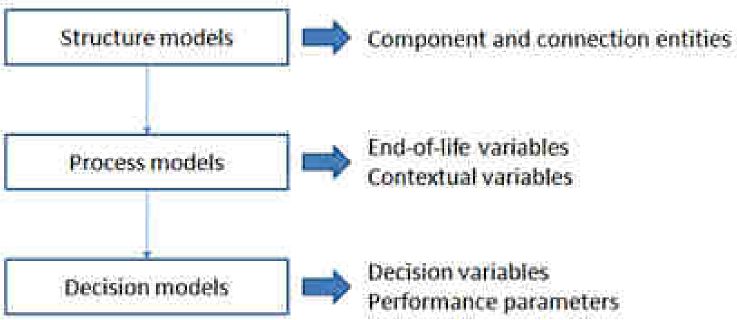


Figure 1. Modelling approach

2.2 Variables of the disassembly process

As we can see, solving disassembly planning problem involves different models and algorithms. Most of the works on this subject we encounter in the literature propose their own method and modelling language. In most cases, the considered approaches do not facilitate the integration of uncertainties. Our goal is not to propose one more approach to solve this problem but to integrate the uncertainties of the disassembly process on the basis of existing models in order to determine an optimal and robust solution. To achieve this objective, we will use concepts and entities utilized by different approaches and then add uncertainties using a modelling language that cope with uncertainties.

The main entities involved in the resolution of the disassembly planning problem are the following:

(i) components: they represent the composition of the end-of-life system and can correspond to parts, subassembly and/or intermediate disassembly states;

(ii) connections: in relation with the component, they complete the structural point of view by representing the joints and/or contact connections as well as relationships between components and subassemblies;

(iii) end-of-life variables: linked with each component, they describe the different recovery actions which can be recycling actions or disassembly operations;

(iv) contextual variables: attached to component and end-of-life variables, they model the recycling actors and other constraints on the recovery actions;

(v) decision variables: related to component and end-of-life variables, they represent the different actions of the decision-maker and give a framework to the decision process;

(vi) performance parameters: attached to end-of-life variables, they describe the consequences of the decision-maker actions.

On the basis of these entities, we propose in Figure 2 the generic framework of the modeling of disassembly planning problem (UML class diagram).

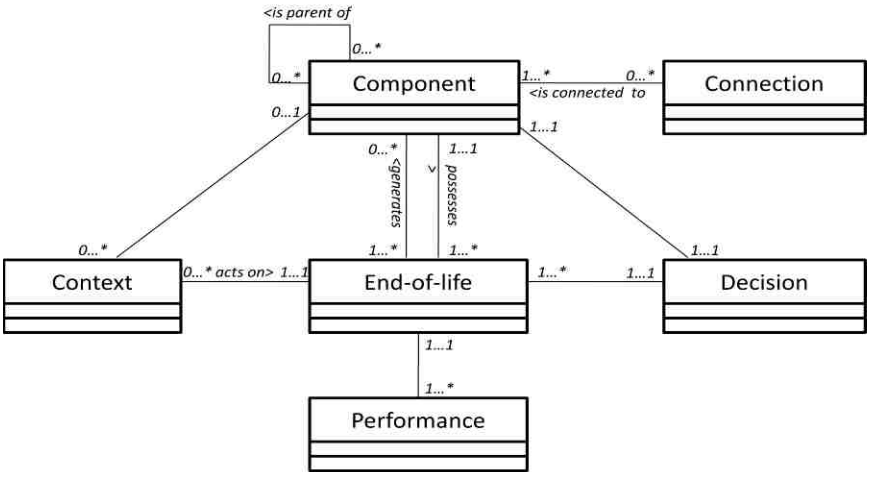


Figure 2. Structure of disassembly variables

At this stage, we have underlined the steps in solving disassembly planning problem and the different variables that decision-makers have to manage. We will introduce now Bayesian network to cope with uncertainties on some of these variables.

3 BAYESIAN NETWORKS FOR DISASSEMBLY PLANNING

3.1 Bayesian networks and influence diagram

We propose to use Bayesian networks as the modelling mathematical tool to solve the following decision problem: *for a given end-of-life system, determine the disassembly levels and sequences on the basis of the process model while taking into account the uncertainties of the disassembly process.*

We use the Bayesian network and their extension to influence diagrams because problems we want to solve have the following features [4]:

(i) they can be represented graphically,

(ii) there is necessity to integrate and manage uncertainties,

(iii) there is necessity to solve an optimal uncertain problem.

The first reason (i) is important in a multi-actors context as in the case of the problem considered here. Indeed, the Bayesian networks and the influence diagrams facilitate the understanding of the problem by all the actors by means of a simple and natural graphical representation. Furthermore, they enable the interaction between these actors and the sharing of knowledge in a unique representation. Indeed, a Bayesian network is a graph model in which knowledge is modeled as variables and each variable correspond to a node in the graph. The directed arcs represent dependence relationship between the variables. The first step in developing a Bayesian network model consists in the elicitation of the interesting variables.

The second point (ii) corresponds to the purpose of our problem approach. The Bayesian networks enable inference that consists in the determination of probabilities for hidden variables of the problem given evidence. When decision-makers think there are uncertainties on some variables, they can evaluate them by probability formulation. Given the knowledge of the stakeholders, these probabilities can be conditional (they depend on some others variables) or marginal.

Once the uncertainties of the disassembly process have been evaluated, decision-makers have to determine the optimal solution according to several criteria. Decision and utility nodes are then added into the Bayesian network that becomes an influence diagram. It models the selection problem of end-of-life options for each component including the utility of these options. In [11] [5], the authors propose inference algorithms that determine the optimal solution.

3.2 Modelling disassembly decision problem using influence diagram

In this work, we propose to use influence diagrams (ID) as a decision tool to model disassembly problem and we suppose that a process model is given. The ID could be used directly to model the process ([4]) but we want to focus in this paper on the decision modelling. We use Disassembly Petri Nets (DPN) to model the disassembly process. The advantages of using Petri Nets in this context are highlighted in [16]. Briefly, the DPN clearly describe the precedence constraints between operations in the disassembly process. The places represent system, components and subassemblies and the transitions represent joints and disassembly actions. The purpose is to represent all the possible sequences of operations. The decision problem is to determine the best sequence according to one or more criteria.

Firstly, our approach will consist in translating the DPN model into a disassembly influence diagram. We illustrate the procedure on Figure 3. The following rules have to be applied:

1) Each place or transition in the DPN is a chance node in the ID (displayed as circles) (Figure 3(a));
2) The variables are linked in the same way in both models;
3) Decision variables are created in the ID whenever a firing conflict is identified in the DPN (Figure 3(b));
4) Utility nodes are created for each transition and end-of-life node.
5) End-of-life nodes are created for each product which represent the end-of-life option (they are noted Ox_P1with x=1,2,… in Figure 3(c));

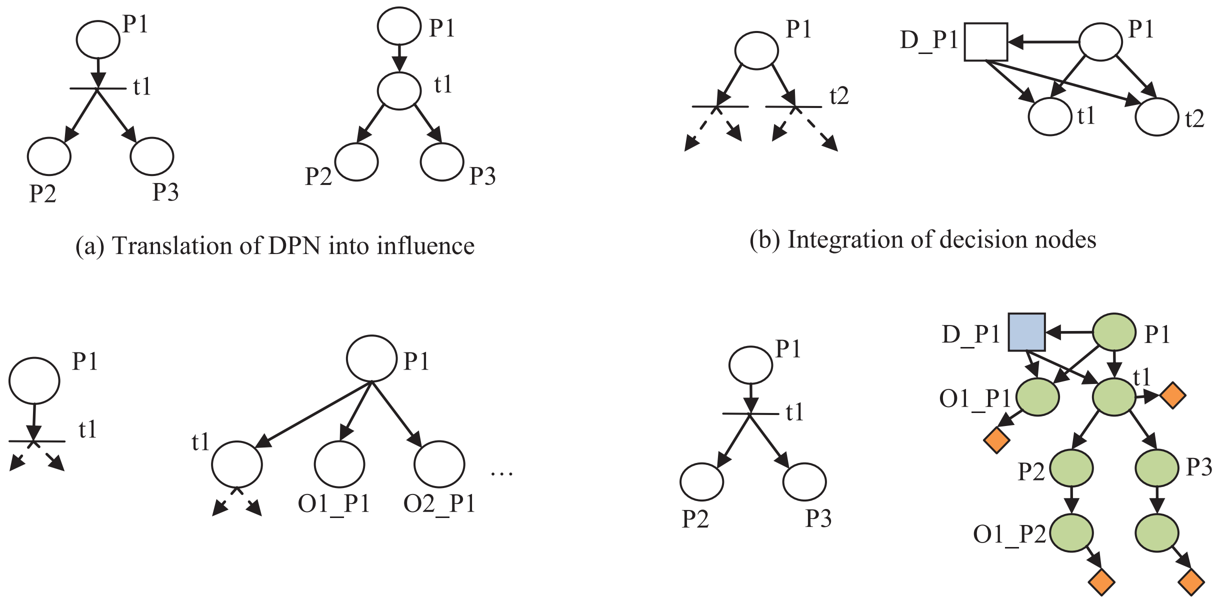
The previous example represents a simple disassembly decision problem that is finally modelled as in Figure 3(c). We have to select the best option between recycling P1 and disassembling P1 (firing t1). The second option implies the recycling of P2 and P3. There is only one end-of-life option for each product. The proposed model looks more complex than the DPN because it takes into account more information into order to solve the decision problem.

Once the graph model has been generated, the variable domains and conditional probability tables (CPT) must be specified. We propose the following states for the place and transition variables:

– non-activate (*na)*: the disassembly option corresponding to the variable is not selected;
– success (*s*): the disassembly option is selected and successes (i.e. the output products are obtained);
– failure (*f*): the disassembly option is selected but fails (i.e. the output products are not obtained or the product is stored waiting for a demand).

Consequences of the state '*f*' are presented in the next part. For the decision nodes, the states correspond to all the disassembly options of the level at which the decision nodes is placed.

At this stage, contextual variables can be integrated to the model to represent the cause of uncertainties. It could be the state of a joint that causes the failure of an operation or the demand for a product that causes the failure of recovery action.



(a) Translation of DPN into influence

(b) Integration of decision nodes

(c) Integration of End-of-life options

(d) Final model

Figure 3. Disassembly process model using influence diagram

The CPT must translate the firing rules of the DPN and integrate uncertainties. For a given place/transition variable, if the uncertainty is directly integrate in the variable (i.e. no contextual variable is used), the CPT is presented on Tableau 1. CPT modelling where p corresponds to the success rate of the recovery action or disassembly operation. The table should be adapted according to the context and graph model.

Tableau 1. CPT modelling

	P		
T	*na*	*s*	*f*
na	1	0	0
s	0	p	1-p
f	1	0	0

This CPT can be associated with the place variable P2 in Figure 3 if *P* corresponds to variable P2 and *T* corresponds to variable t1. The translation of the DPN firing mechanisms into the CPT is presented here:

1) for transition variables t_i in the ID which correspond to the transition nodes t_i in the DPN:
   a) state *na* (in ID) means that the transition (in DPN) cannot be fired or can be fired but we don't decide to (conflict resolution);
   b) state *s* means that t_i can be fired and is fired (token are moved from input place to output place);
   c) state *f* means that t_i can be fired but fails (not fired);
2) for place variables P_i in the ID which correspond to the transition nodes P_i in the DPN:
   a) state *na* means that there is no token in the place;
   b) states *s* and F means there is a token in the place and the output transition are not fired.

Once we have translated the DPN behaviour mechanisms into the CPT of ID variables (i.e. process model into decision model), we have to determine the states (retrieved components, subassemblies, joint states …) of the disassembly process according to different decision's configurations.

3.3 Evaluation of disassembly solutions

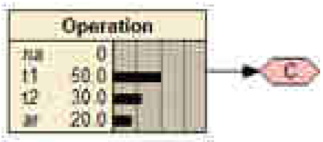
Disassembly solutions are evaluated by means of utility nodes in the ID. They model the economical performance of the different recovery actions and disassembly operations. ID models enable the integration of utility in table forms as presented in Tableau **2**. There are three types of nodes:

- disassembly cost nodes: linked to disassembly operation node, their value is function of disassembly operation realization,
- recycling cost nodes: they evaluate each recycling action realization mode of recycling node to which they are linked,
- recycling revenue nodes: they model economical flow that is generated when a recycling option is validated.

Tableau 2. Performance parameters

	P_i			
	na	*s*	*f*	
Utility	*0*	*r_i*	*cf_i*	r_i: profit of the recovery action associated with P_i
	t_j			cf_i: cost of the failure of recovery or disassembly actions
	na	*s*	*f*	c_j: cost of the disassembly action
Utility	*0*	*c_j*	*cf_j*	

An example of an evaluation of an operation is given on Figure **4**. A cost parameter is associated with each realisation mode of the operation (*t1* and *t2* correspond to different duration and *ar* correspond to stoppage). Given the uncertainty on the operation realization, this operation is evaluated through expected utility calculation.



	Operation			
	na	t1	t2	ar
utility	0	c1	c2	c3

Expected utility of operation:
*EU(Operation) = Pr(t1)*c1 + Pr(t2)*c2 +*

Figure 4. Evaluation of a disassembly operation

These different utility nodes allow optimization of a criterion for selecting a disassembly plan. This criterion is decomposed at each product in order to select the option or operation for each of them. To achieve this goal, decision node of each product indicates the evaluation of each option. The decision rule consists in selecting the option that maximise the expected utility of the product and it is called end-of-life policy.

The set of all polities forms the strategy. It gives the products that have to be generated from the end-of-life system, the recycling options for these products and the disassembly operations that are needed to generate them.

The purpose of optimization method is to determine the strategy for a given end-of-life system. There are different methods to solve decision graph (see [5] for a presentation). In [11], the authors propose an algorithm to solve multistage decision problem represented as influence diagram. We use this algorithm which is implemented in BNT, a bayesian network toolbox for MATLAB (see [13] for the presentation of the algorithms used in this toolbox).

3.4 Predictive or reactive disassembly strategy

As we mentioned before, the disassembly strategies with uncertainties can be predictive or reactive. The advantage of disassembly ID is that it can manage the both cases. This is due to the fact that we can enter observation on the state of variables in the network as evidence. In a predictive context, no observation is made on variables and the optimal sequence is determined before the beginning of the process. The reactive case is encountered when the process has begun and a disassembly operation fails. The user may want to search a new sequence from the operations that have already been made. He can enter the following observations on transition variables:

1) $t_i = s$ for the operations that succeed,
2) $t_i = f$ for the operations that failed.

The searching for an alternative sequence takes into account these observations. Others observations could be integrated as contextual variables such as the state of a joint that might cause the failure of an operation.

In both predictive and reactive disassembly strategy, the user must determine the success rates of disassembly operations and the probability of demand for recovery products. For the case of disassembly operations, the success rate can be evaluated by the record of total number of success, $N_t^{'}$, divided by the total number of execution, N_t, as presented in [16]. Then $p(t_i) = N_t^{'}/N_t$. Parameter learning algorithms in Bayesian networks could also be used. Some of them are presented in [14][13] for instance.

4 APPLICATION EXAMPLE

We use a telephone example to illustrate our approach of disassembly planning. It is extracted from [2] or [16] where the authors propose a DPN to model the disassembly process that is presented in Figure 5. The telephone product consists of four parts A, B, C, D. The place P1 represents the first assembly state and P2, P3, P4 represent subassemblies. The parts are represented by P5, P6, P7, and P8. The transitions represent operations which consist in this example of removing joints. The end-of-life values and operation costs are denoted by r_i and c_i (see Figure 5 for numerical values). As explained before, the DPN displays the precedence constraints between operations.

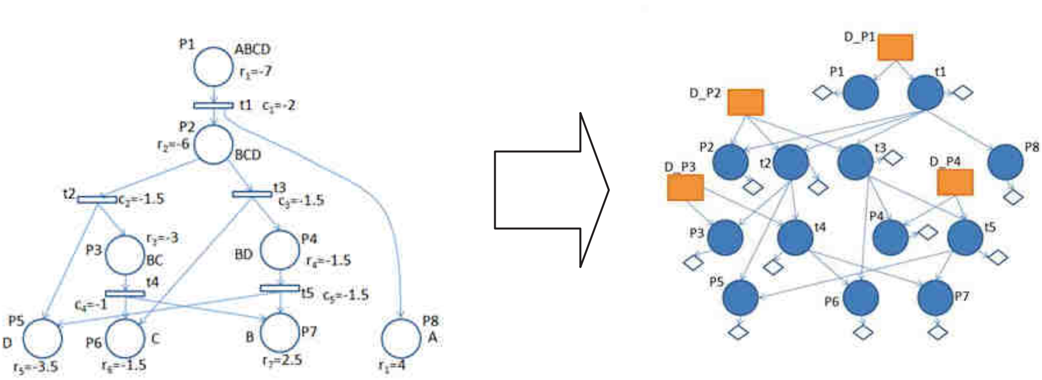


Figure 5. Disassembly models of a telephone

We apply the transformation rules presented in this paper to obtain the ID model illustrated in Figure 5. The names of the variables correspond to the node's names of the DPN. We can see that there are four decisions nodes and each configuration of the decision node values is a disassembly solution. In fact, some configurations are the same due to the fact that when we stop the disassembly process at an intermediate stage, the successor decisions node are not necessary. Indeed, we want to determine disassembly level and sequence so P_i variables means that the associated component is recovered (selected by means of D_P_i variable) and the disassembly process can stop here.

We apply the solving algorithm for the case with non uncertain data (p=1 in the CPT of disassembly variables) and we obtain the following result:

1) Disassembly sequence: t1 – t3;
2) Disassembly level: {P4, P6, P8};
3) MEU = -2.5.

This result is not the same as in [12] since these authors add a constraint: parts A and D must be reused at the material level. We add this constraint in the ID by entering evidence to forbid the activation of the subassemblies containing A and D. We enter then P1 = NA, P2 = NA and P4 = NA. We obtain the same result as in [12]:

1) Disassembly sequence: t1 – t2 – t4;
2) Disassembly level: {P5, P6, P7, P8};
3) MEU = -3.

In the same way, we can manage a reactive disassembly strategy. If operation t3 fails, we determine an alternative sequence after entering t3 = na. The solution is then the same as the later.

Tableau 3. Success rate of operations

	t1	t2	t3	t4	t5
p	0.9	0.95	0.8	0.9	0.95

When applying a predictive disassembly strategy, the parameters p_k have to be learnt for each disassembly variable (P_k or t_k). To test our approach, we arbitrary set up parameters for CPT corresponding to transition nodes and we only enter uncertainties on disassembly operations. They are displayed on Tableau 1. CPT modelling. For the cost parameters, we consider here that the failure of an operation t_j implies the stop of the process on the predecessor P_i variable: $cf_j = r_i + c_j$. Indeed, in this example, all the utility of intermediate sub-assembly are negative.

The result of disassembly sequence and level is the same as the first one but with MEU = -3.29. Although the success rate of t2 is superior to that of t3, the optimal strategy takes t3. This is due to the important negative utility of P3 (BC) with regard to P4 (BD). If we had used the failure risk of the disassembly sequence as criteria, it could have been more interesting to take t2 instead of t3. Others criteria can be use to determine the optimal disassembly strategy such as inventory cost or demand for recovered products.

5 CONCLUSION

In this paper, we present an approach to cope with uncertainty in disassembly planning process. We propose to use Bayesian network and their extension to influence diagram as the underlying tool. The influence diagram model can either be constructed directly from the problem specification or be a translation of a Petri Net model. Our method consists in translating Disassembly Petri Net (DPN) into influence diagram to determine the disassembly strategy. We have tested this approach on an example of the literature. Future researches include the integration of multi-criteria approaches to solve the decision problem. Furthermore, we want to automate the translation from DPN to influence diagrams to decrease the modeling effort.

6 REFERENCES

[1] Chen S., Oliver J., Chou S. 1997 Parallel disassembly by onion peeling. Journal of Mechanical Design, 119 (2), 267-274.
[2] Dutta L. (2006) Contribution à l'étude de la conduite des systèmes de désassemblage, PhD. Dissertation, Université de Franche-Comté, France.
[3] Geiger D., Zussman E (1997) Probabilistic Reactive Disassembly Planning, Annals of the CIRP, 45(1), 49-52.
[4] Godichaud M. (2009) Outils d'aide la décision pour la sélection des filières de valorisation des produits de la déconstruction des systèmes en fin de vie : application au domaine aéronautique, PhD. Dissertation, Université de Toulouse, France.
[5] Jensen F.V., Nielsen T.D. (2007) Bayesian network and decision graph, Springer.
[6] Kanai. S, Sasaki. R., Kishinami. T. (1999) Representation of Product and Processes for Planning Disassembly, Shredding, and Material Sorting based on Graphs, Proceedings of IEEE International Symposium on Assembly and Task Planning, Port, Portugal, 123-128.
[7] Kang J-G (2005) Non-linear disassembly planning for increasing the end-of-life value of products, Ph.D. dissertation, Ecole Polytechnique de Lausanne.
[8] Lambert A.J.D. (1999) Linear Programming in Disassembly/Clustering Sequence Generation, Computers and Industrial Engineering, 36(4), 723-738.
[9] Laperrière L., Elmaraghy H. (1992) Planning of products assembly and disassembly, Annals of the CIRP, vol. 41(1), 5-9.
[10] Martinez M., Pham V. H., Favrel J. (1997) Dynamic Generation of Disassembly Sequences, Proceedings of 6th International Conference on EngineeringTechnologies and Factory Automation, 177-182.
[11] S. Lauritzen, Nilsson D. (2001) Representing and solving decision problems with limited information, Management Science, 47(9), 1235-1251.
[12] Moore K., Gungor A. (1998) Gupta S. Disassembly Petri net generation in the presence of XOR precedence relationships, Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics, San Diego, California, 13-18.
[13] Murphy K.P. (2002) Dynamic Bayesian Networks: Representation, Inference and learning, Ph.D. Thesis, University of California, Berkeley.
[14] Naïm P., Wuillemen P-H., Leray P., Pourret O., Becker A. (1999) Réseaux Bayésiens, Eyrolles.
[15] Sanchoy, K. D., Sandeep N. (2002) Process planning for product disassembly, International Journal of Production Research **40**(6), 1335-1355.
[16] Zussman E., Zhou M. (1999) A methodology for modeling and adaptative planning of disassembly processes, IEEE Trans. Robotics and Automation, 15(1) , 190-194.