Generating the optimal process structure for decision sequences by Separation Network Synthesis

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Abstract — **In this paper it is examined whether efficiency improvements and cost reductions could be achieved by changing the order of certain predefined tasks in decision processes. A method has been developed based on log analysis and mathematical modelling. A Separation Network Synthesis (SNS) model has been constructed from the business process related historical data, and extended by further constraints for resource parameters and prerequisites. By transforming the model to a Process Network Synthesis (PNS) problem, optimal and alternative suboptimal structures, i.e., decision sequences can be generated and global optimality can be guaranteed.**

Keywords: Optimization, P-graph, Business Process, Process Synthesis, Decision Network

I. Introduction

Operation of companies highly relies on their precisely defined internal processes. Each process has a list of tasks with dependencies and required resources. The process flow is affected by the results of decisions implied in the processes, or in a more complex situation, a network of decisions. This approach has led to a stable and balanced operation, but unfortunately the processes are mostly described based on past experience without investigation on their optimality and cost effectiveness. It is also likely that these processes are not adjusted to the changes of resource cost or availability, which can lead to further inefficiencies during operation.

II. Methodology: SNS by PNS

Separation-Network Synthesis aims at determining the optimal sequence of operations from multicomponent mixtures by separations, mixing, and divisions, leading to a series of products of predefined compositions at the end. Separators can select certain components and distinguish them from others. Mixers can merge mixtures of any compositions, while dividers can share mixtures between multiple operations without changing their compositions. To explore all the potential separation sequences, first a rigorous superstructure is constructed, which incorporates all the possible separation sequences as its parts [1]. Then an optimization model can select the optimal part of it.

Process Network Synthesis (PNS) is a complete optimization framework for designing process structures or flowsheets from a set of raw materials (resources) and candidate operating units (activities) to achieve the set of desired products (outcomes). By the help of the corresponding combinatorial algorithms it can provide not only a single optimal process structure, as most optimization software do, but a series of best optimal and suboptimal process structures [2]. As a result, process designers can compare and select the most appropriate process structure for their purposes.

In the current paper a methodology is proposed, where decision sequences in business processes are formulated as a Separation Network Synthesis problem, and then optimal and alternative best networks are computed by PNS algorithms and software. The methodology is illustrated by a real life case study of restructuring a procurement process.

III. Case Study

In business processes decisions need to be made by answering a questions which can have multiple answers, and costs which cover their evaluations. A decision network is defined by a set of decisions and their dependencies. By evaluating historical data, the probabilities of occurrences can be determined for each decision sequence. The aim is to determine the cost optimal decision network, which results proper outcomes with minimal average resource utilization. For demonstration, we have analyzed a procurement decision process.

A. Questions and costs

The network contains 3 questions, each of them with 2 possible answers, Yes or No respectively. An evaluation cost is also given for every question. Data for the example can be found in Table 1.

Question	Cost	Result
Q1: Centralized procurement?	200	Yes
		No
Q2: Is it in the budget?	100	Yes
		No
Q3: Approved?	300	Yes
		No

Table 1. Given questions with parameters

B. Structure of the problem

Based on the current process, a network can be constructed from the questions, which describes the dependencies among the questions. The network in Figure 1. is the currently applied process for the procurement.

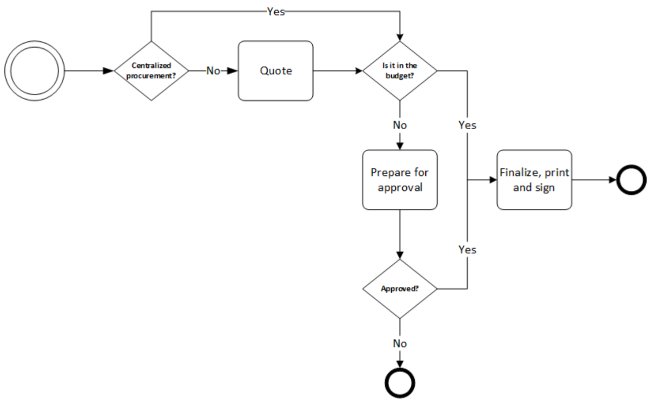

Figure 1. Structure of the original decision network

C. Occurrences

The 3 questions may result 8 different combinations of answers. From the analysis of historical data, the occurrence of each possible scenario can be estimated and it can be found in Table 2.

Case	Q1	Q2	Q3	#
P1	Yes	Yes	Yes	30
P2	No	Yes	Yes	20
P3	Yes	No	Yes	24
P4	No	No	Yes	16
P5	Yes	Yes	No	0
P6	No	Yes	No	0
P7	Yes	No	No	6
P8	No	No	No	4

Table 2. Potential cases with occurrences

D. Outcomes

It is possible that different result combinations lead to the same outcome. Each outcome in Table 3. is defined by a set of result combinations.

Outcome	Cases	
Fail	P7	P8
Procurement	P2	P4
Price list	P1	P3
Impossible	P5	P6

Table 3. Potential outcomes formed from cases

IV. Modell Transformation

In previous studies it was shown that SNS problems with multiple separation techniques [3] can be handled and solved efficiently as PNS problems [4]. Hereby I introduce our method to transform decision networks into SNS problem.

A. Analogy between Decision Networks and SNS

By examining the problem classes, similarities can be found. Each decision is equivalent with a 1 input multiple output sharp separator. Both has its own input which get processed into previously defined outcomes based on an examined property. The property in this case is the answer for a given question. By translating these terms to PNS, every decision can be represented by an operating unit, and every possible scenario set can be handled as a material. Every operating unit has a single input representing a case set, and these cases are classified into two outputs according to the answers replied for the question represented by the operation.

B. Steps of the model transformation

The proposed model transformation algorithm contains 3 main steps, which are the followings:

1. Define the raw material: In the first step, the raw material needs to be constructed. Each structure will contains only 1 raw material, which contains the mixture of every case from the original problem for which the probability is more than zero.
2. Define the products: Every Outcome represents a product in the structure. In the second step these product materials needs to be constructed.
3. Add operating units and intermediate materials

Operating units and intermediate materials are added in a recursive method, starting from the raw material. For each material an operating unit need to be added every time the material represents cases with different potential outcomes. The operating units input material will be the examined material, and the output materials need to be constructed from the input by dividing it into two new set of cases by the different answers. The newly created output materials are also need to be examined recursively until new intermediate materials are created.

C. Assign costs

Cost only appears for operating units. For each operating unit a proportional cost assigned, which is equal with the questions cost multiplied by the sum of the occurrences of the possible cases represented by the input material.

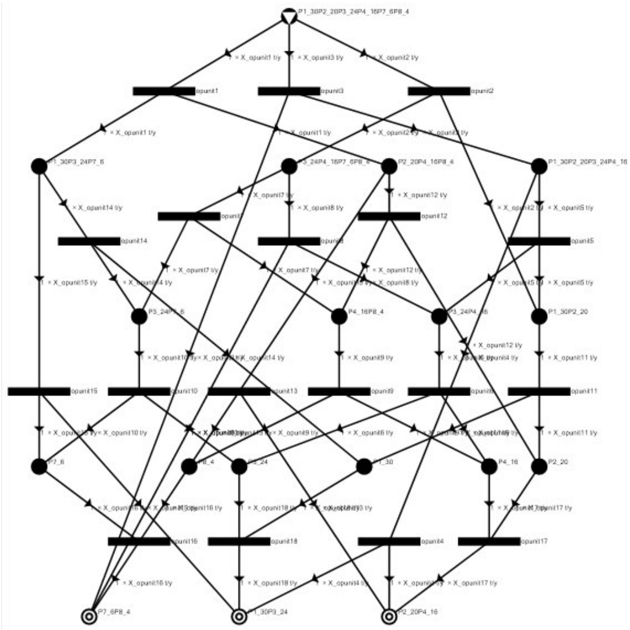

Figure 2. Generated P-graph model

D. *Result of the model transformation for the example*

The model transformation for the case study has led to a single raw material, 3 products, and 15 operating units with 14 intermediate materials. After connecting them, the superstructure represented by P-graph can be seen in Figure 2.

V. RESULTS

The initial structure cost is 45,000. By Software P-graph Studio [3] the generated PNS problem can be solved efficiently. 8 structurally different solution structures had been computed by the algorithm ABB.

Number of Solution	Total Cost
1	43,000
2	45,000
3	45,000
4	47,000
5	48,000
6	48,000
7	50,000
8	57,000

Table 4. The generated solutions with total cost

A solution structure had been found with better cost than the initial structure resulting a potential of 4.4% cost saving. The cost optimal solutions' P-graph representation can be found in Figure 3.

After identifying the cost optimal structure, the P-graph representation can be transformed back to the business process of the decision network. The optimal decision network can be seen in Figure 4.

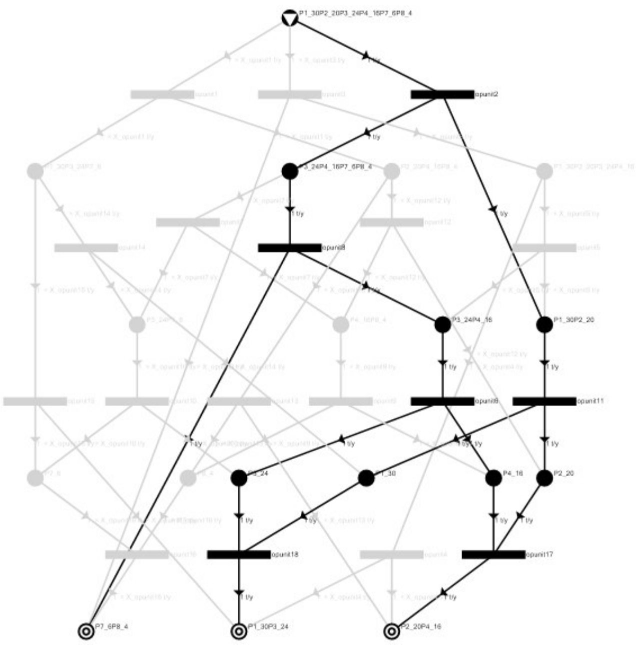

Figure 3. Cost optimal solution

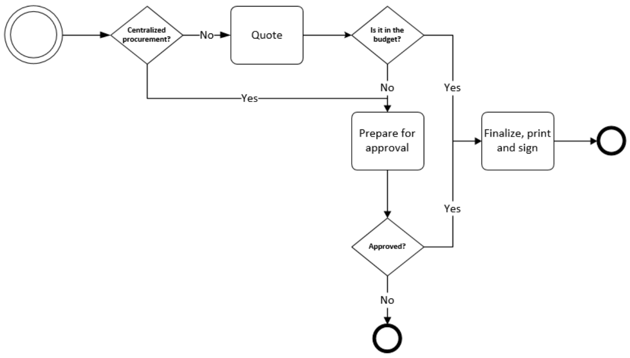

Figure 4. Optimal decision structure for cost optimal solution

VI. CONCLUSION

By the help of the proposed algorithmic method, the efficiency and optimality of the applied decision mechanism can be examined automatically at any time. The deviation from the optimum can be measured, and the best decision order or network in the given situation can be regenerated automatically.

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