# DESIGN PROCESS MODEL FOR OPTIMIZING DESIGN OF CONTINUOUS PRODUCTION PROCESSES

Mika Strömman, Ilkka Seilonen, Jukka Peltola and Kari Koskinen
*School of Electrical Engineering, Aalto University, Espoo, Finland*

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Abstract: The non-growing market situation in pulp and paper industry has tightened the competition. Cutting the design costs by integrating design activities is not going to be enough but the design itself has to be improved. The design of continuous production processes can be enhanced by utilizing optimization techniques during the design process. The benefit of the optimization techniques in process design depends on adequate usage of them during the design process. However, this paradigm shift will require changes in the existing design processes. In this study, the required changes are identified and a new design process model describing the optimizing design utilization is developed. The model is then assessed through a case study and an interview study to ensure that the design process can be realized in the conceptual design phase of a real delivery project.

## 1 INTRODUCTION

The market situation in pulp and paper industry have is setting requirements for the design methods. The design process itself has to be conducted efficiently, but in the last years the costs has already been cut off with better project management and concurrent engineering. One possibility for rationalization lies in the design itself; traditionally, the design of the plant is more oriented into structural design and less to the optimal combination of operational and structural design. The design problem can be formulated as a bi-level multi-objective optimization problem (BLMOO). Mathematical methods for solving BLMOO problems exists and the method have been applied in process facility design in research projects.

However, the utilization of such optimization methods requires enhancement of the engineering process so that the required information for optimization is available on the right time and the results of optimization can be used in design. A design process describing optimizing design of continuous production processes hasn’t been thus far presented and it is a necessity for adopting BLMOO-methods in real delivery projects.

This research has been conducted as a part of a larger research project in which the objective is to develop a new optimization based method for designing a process plant. Our part of the research is to define a model for optimizing design process and assess the usability of that model. The research methods of this study include experimental definition of a business process model, case study (with the model) and interview study evaluating the properties of the model.

In the first chapter the related work and state of the art is discussed. The following chapter presents the new engineering business process which takes into account the optimizing method. Next, a case evaluating the new engineering business process is presented and the observations based on expert interviews are discussed.

## 2 PROCESS DESIGN AND OPTIMIZATION

### 2.1 Design of Continuous Production Systems

A process plant design is a multidisciplinary process (process design, automation, software etc.) (Watermeyer, 2002). Traditionally the process plant design process has been water fall model like linear process with stages ending to document deliveries.


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In a delivery project, the deadlines are counted backwards from the day that the plant should be operational. The length of work phases are determined based on time needed for work and procurement (Cziner, 2006).

The plant engineering process can be divided into steps e.g. problem analysis, conceptual design, detailed engineering, and construction (Tuomaala, 2006). More business oriented divisions are also possible, for example conceptual phase, pre-feasibility study, feasibility study, investment decision and implementation (Diesen, 2007). Although all the phases are equally important for reaching the goal, the focus in this research is put on the conceptual design phase, because the optimization methods researched in this research project aim to solve problems on conceptual design level. Other phases of the engineering process are relevant to our research in that sense that the tools and methods should be compatible to the proposed changes.

In the conceptual design phase a very small amount of information is available and the time and resources are limited (Seuranen, 2006). Still the decisions in this phase fix 80% of the total costs of the project (Douglas, 1988). Decisions in the early phases of the project are also quality-critical, because the costs of changes increase tenfold in each phase (research – process flow – final design – production) (Bollinger, 1996). In process plant engineering, the conceptual design phase is led by process design. All the other engineering disciplines are more or less in consulting role. For these reasons, the greatest advantages can be achieved in early phases of the business process.

Because of the shortened delivery times, the other engineering disciplines have to begin their work before the process design is ready. The saving using concurrent engineering is calculated to be up to 50% of the calendar time in a delivery project (Bañares-Alcantara, 2005).

The sub-processes of any process design task are design task definition, process structure design, process operation design an design acceptance. Process structure design and process control design interact and should therefore be designed simultaneously (Pajula, 2006). The existing process design approaches can be divided to heuristic and engineering experience based methods, optimization based methods and case-based reasoning methods (Seuranen, Pajula and Hurme 2001). Case based reasoning (CBR) has been applied for design of the pulp process. The main challenge in CBR is the need of extensive database to provide the required knowledge (Pajula, 2006). Outsourcing of the design work is a common practice nowadays. Fathianathan and Panchal (2009) have proposed a model to support outsourcing decisions.

## 2.2 Optimization in Process Design

Current work practices in forest industry process engineering are almost solely based on engineering experience. Simulation and optimization is used in the design of unit processes, but less in the design of the process as whole. Plant wide simulation enables the validation of process structure and control concepts even before selecting suppliers and therefore it reduces risks (Ylén, et al, 2005) and gives a deeper understanding of the process (Pulkkinen, Ihalainen and Ritala, 2003). According to the interviews, plant wide simulation is more useful when building a plant with totally new concepts when the “rules of thumb” are not available.

For combining the optimization of plant structure and plant control, there are several options. Optimization strategy can be sequential, iterative, bi-level or simultaneous. (Fathy, Reyer, Papalambros and Ulsoy, 2001).

Bi-level optimization has been under an active research lately (Dempe, 2002). Still only a few research is dealing with multi-objective bilevel problems. Eichfelder (2010) presents an algorithm for solving bilevel multi-objective problems. The combination of dynamic simulator model and dynamic optimization has been researched for papermaking process (Linnala, et al, 2011).

## 2.3 Information Systems for Process Design

The variety of the Computer Aided Engineering (CAE) tools supporting process systems engineering (PSE) is enormous. One of the interviewed engineering enterprises is using over 50 different engineering tools. A trend, as seen in modern integrated process engineering tools, is the transformation from document-centric design to data-centric design, realized with database technology (Comos, 2011),(Smart Plant, 2011), (Bentley, 2011). Major tool vendors have developed, acquired and integrated engineering tools from other engineering disciplines under unified product families. Modern process engineering support systems combine modeling and information management features for engineering of many aspects of plant engineering, e.g. process, piping, electrical and instrumentation, 3D layout, equipment lists, part data sheets, etc, thus comprising an integrated plant information model. This also enables advanced change management, where modification of an object through one view notifies users of other views, looking at the same object. Multi site work flow management is featured for both engineering and commissioning. Integration to external CAE tools is possible through export and import interfaces using standard or proprietary data formats. An important prerequisite for cost efficient integrated engineering is the use of common data models defined in the standards. ISO 15926, "lifecycle data for process plant" (ISO 15926) is a standard dedicated to the process industry, widely accepted by tool vendors. It has a central role in pursuing information interoperability between engineering systems and it is used in many plant information exchange tool initiatives, such as iRing (iRing 2011) and XMpLant (XMpLant, 2011) and even as a native data model of a plant modeling tool (Bentley, 2011).

Plant information models and semantic technologies have induced much academic research. For example, POSC Caesar association (POSC Caesar, 2011) assembles R&D around the ISO 15926 and modeling methods, such as (Batres, et al, 2007). However, Wiesner, Morbach and Marquardt. (2010) questions whether a single global plant information standard is a realistic goal in the first place and suggest a semantic integration framework OntoCAPE.

# 3 MODEL FOR OPTIMIZING DESIGN PROCESS

Optimizing process design is here modelled in terms of a business process model. The model describes the stakeholders of the optimizing process design and their activities together with the data, knowledge and utilized mathematical models. Based on these the requirements for IT support are identified.

Process design as an optimization problem

The process design task can be considered as an optimization problem. There are a few general requirements for the process. The process must be operable, reliable and yield products of sufficient quality with minimum operational cost. On the other hand the investment and maintenance cost of the process should be minimized as well. On this basis it is natural to consider and model the design problem as a bi-level multi-objective optimization problem. The mathematical representation of the general bi-level multi-objective optimization problem is:

$$
\begin{aligned}
&\min_{(x_u, x_l)} F(x) = (F_1(x), \ldots F_M(x)), \\
&\textit{subject to} \quad x_l \in \arg\min_{(x_l)} \left\{ f_1(x), \ldots, f_{m(x))} \middle| g(x) \geq 0, h(x) = 0 \right\}, \\
&G(x) \geq 0, H(x) = 0, \\
&x_i^{(L)} \leq x_i \leq x_i^{(U)}, i = 1, \ldots, n. \qquad (1)
\end{aligned}
$$

where

**F**(x) are the upper level objective functions,

**f**(x) the lower level objective functions,

**G**(x), **g**(x), **H**(x) and **h**(x) the upper and lower level inequality and equality constraints. (Dep and Sinha, 2008)

There are multiple methods for solving bi-level multi-objective optimization (BLMOO) problems (Eichfelder, 2010) and (Branke, Dep, Miettinen, Slowinski, 2008) and the solution method should be chosen according to the problem itself and the possibilities for interaction with the decision maker (Miettinen, 1999). In the plant design process, there is a logical division to optimization levels, so that plant structure is the upper level (**F**(x)) and the operation of the plant is the lower level (**G**(x)). The nature of the plant design is also multi-objetive; the balancing between design parameters as for example the total cost of the plant, operational costs, production quality, production volume and expected oee-value is difficult and the decision of these values belongs to the plant owner, not the designer. Therefore the gathered requirements should also cover business oriented user preferences.

In this research the solution of the optimization problem was simplified by scalarizing the lower level optimization problem, but this simplification has no affect to this part of the research focusing on the business process of the design.

## 3.1 Stakeholders

In the model of optimizing design, new stakeholders, an optimizer and a modeler, are added to the group of stakeholders involved in process design as illustrated in Figure 1. The optimizer is an expert of mathematical optimization whose responsibility is to help the process designer in finding more optimal process designs. The optimizer also needs to cooperate with the modeler in order to be able to take into account the operational aspects of the designed process. These cooperation connections with the optimizer will also change the work of the process designer and modeler. Successful cooperation between the stakeholders is a necessity for useful design optimization.

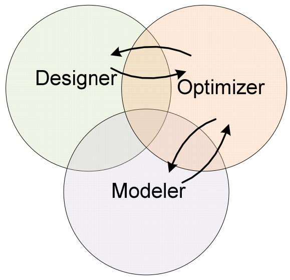


Figure 1: Stakeholders of optimizing design.

The role of the optimizer can be described as an analyst 0. His responsibility is not to make decisions about process designs but to produce useful information for the designer about possibly better designs. In order to do this, the optimizer will need to have expertise in multi-objective optimization and familiarity in process design. The adoption of optimization also changes the roles of preexisting stakeholders. Designer is the decision-maker of the process design and the client of the optimizer. In optimizing design the designer has to select a part of his design problem for optimization together with the optimizer. In addition to this, the designer also has to cooperate with the optimizer during the optimization process and finally interpret the results and decide how to apply them. Again, the optimizer will become the client of the modeler.

In order to adopt the new business process, all the stakeholders should gain some advantage of the enhanced business process. The process designer gains competitive advantage by offering design that is more tailored and more cost effective along the life cycle of the plant. For the optimizer and modeler, the new model opens a totally new business possibility.

## 3.2 Business Processes

Dynamic and stochastic nature. In this subtask the designer and the optimizer can rely on the expertise In the model of optimizing design the activities of process design have partially changed. The basis for the activities is the existing design processes that are extended and partly modified. The suitable time for optimization is the conceptual design phase. When the designer identifies a need for optimization in his conceptual design, he initiates cooperation with the optimizer. During this cooperation an optimal design balancing both structural and operational aspects of the design are being searched for. This process can be described as expert cooperation in which also the modeler will be included.

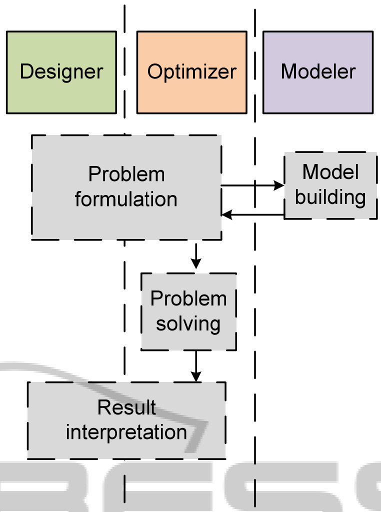


Figure 2: Activities of optimizing design.

The optimization activities take place in a few stages as an extension to conceptual process design phase as illustrated in Figure 2. The process starts from optimization problem definition and continues through optimization problem-solving until result interpretation. During these stages different cooperation patterns between the designer, optimizer and modeler are needed. The whole process and each of its stages may also be iterative.

The purpose of the optimization problem definition is to define a part of the designer's design problem as BLMOO for the optimizer. This stage is performed by the designer and optimizer together. The designer identifies parts of the overall design problem in which balancing structural and operational aspects of the design is essential. The solvability of the problem is then assessed by the optimizer, designer and modeler together. The assessment requires expertise of all three stakeholders because the result depends not only on the problem itself but e.g. optimization tools, process models and data about the process. Eventually the designer and the optimizer should agree on a useful and solvable design optimization problem, which the optimizer then formulates as a BLMOO problem.

An important subtask of the optimization problem definition is process operation modeling. Modeling the operational part of the design problem is much more difficult than the structural part due to its of the modeler. The modeler is expected to have expertise about both mathematical modeling and the designed process itself, i.e. its chemical and physical characteristics. Based on his expertise the modeler should be able to create such operational models that are suitable to be used in optimization. The suitability of the models will be assessed by the optimizer and the designer.

The stage of problem-solving is focused on the optimizer. However, cooperation with the other stakeholders is likely to be needed also in this stage. In the beginning of this stage the data and models required in the optimization are expected to be transferred to the optimizer in a form which he can utilize. Depending on the utilized MOO method, different type and amount of cooperation with designer will be needed also during the actual problem-solving. According to an interview (see chapter "Interviews") industrial experts seem to favor optimization methods which lead to representations of Pareto optimal designs.

The last stage of optimizing design is result interpretation. Also this stage is performed in cooperation between the designer and the optimizer. The optimizer prepares result presentations, which indicate Pareto optimal designs and help the designer evaluate the impact of his preferences on the design. The designer is expected to study the design optimization result, assess its reliability and make decision about possible changes to his design. This is not necessary a straightforward task and is likely to require assistance from the optimizer and the modeler. The reliability of the optimization result is dependent on used operational models and data. Sensitivity analysis of the result might also be needed. In the end, the designer can adopt changes to his design or reject the optimization results and reformulate the optimization problem with the optimizer.

## 3.3 Data, Knowledge and Models

The optimizing design requires additional knowledge, data and models than the state-of-the-art approaches to process design. The new requirements originate from the need to solve the process design BLMOO problem. The new requirements for knowledge, data and models in optimizing design are summarized in Table 1. In addition to these, the previous requirements are still valid, e.g. designer knowledge for process design, use of design data and design models.

The expertise and knowledge of the stakeholders involved in optimizing design is complementary. The designer has knowledge about industrial processes and their design, customer requirements and evaluation of process designs. Meanwhile, the modeler is expected have knowledge about similar processes and their mathematical modeling.

Table 1: Knowledge, model and data requirements in optimizing design.

| | Knowledge | Data | Models |
|---|---|---|---|
| Designer | Process design, process knowledge, some understanding about optimization | Design data, customer requirements | Flow diagram<br>P&ID<br>Plant Model |
| Optimizer | Optimization, some understanding about design | Design data and operational data from designer and modeler | Operational and design level problem formulation models for optimization |
| Modeler | Modeling, Process knowledge | Operational data, some design data | Operational models (e.g break probability model, |

The knowledge of the optimizer concerns about optimization and acting as an analyst in a decision-making process of MOO. However, during the activities of the optimizing design combination of the knowledge of different stakeholders and knowledge transfer between them is necessary. A partially common understanding of the design problem shared by the stakeholders has to be created (Konda, Monarch, Sargent and Subrahmanian, 1992). This is may be done according to the BLMOO of the process design.

Mathematical models of the designed process have an important role in optimizing design. Models are needed particularly for modeling the operation of the process. Mathematical models have been used in the design of continuous processes also previously, e.g. in simulations (Ylén, et al, 2005), but these models are not necessary suitable to be used in optimizing design. In order to be able to be utilized in optimizing design, the operational models need to have a suitable balance of modeling capability and computational requirements. The computational requirements can be met by modeling only selected parts of the process. More precise models may be utilized after the design in a design validation stage.

The optimizing design requires data transfer between the optimizer and other stakeholders, which is not needed without optimization. The most important data transfer takes place from the designer to the optimizer. The designer has to pass the most of the data describing the design optimization problem to the optimizer, e.g. flow diagrams, dimensions of equipments etc. The other source of data to the optimizer is the modeler. He is expected to deliver to the optimizer the operational models and the data required by them, e.g. model describing the probability of break. This data is intended for algorithmic processing, which indicates a requirement for adequate precision. The final data transfer consists of the optimization results, which are passed from the optimizer to the designer. This data has a form of a document. A major requirement for it is understandability.

### 3.4 Requirements for Information Systems

The new requirements for the information systems mainly rise from the new data flows between designer, optimizer and modeler. The amount of data from the designer's plant model can be quite huge, so the optimizer should have access to the designers plant model tool to be able to import the needed set of design data. A new thing is that the designer should also include the constraints of the design to the model when applicable. The design data should be transferable to optimizing tool as well as the models that the modeler has created. The support for representing the alternatives to the designer is not that critical, because that document should be kept brief and simple.

## 4 ASSESSMENT OF THE MODEL

In this chapter, the business process model of optimizing design is assessed through a small-scale case study. This case study was carried out as a part of a wider research project and the results of the mathematical solution of the BLMOO in this case can be found in our partners' publications (Ropponen et al., 2010), (Eskelinen, et al., 2010), (Ropponen et al., 2011) and (Ropponen, Rajala, Ritala, 2011). The case was evaluated by internal review and expert interviews.

### 4.1 Case Study

#### 4.1.1 Case Design Problem

The design task in the case study was to dimension six storage towers of a part of a paper-making process and to guarantee the runnability and stability of the process. The dimensioned storage towers

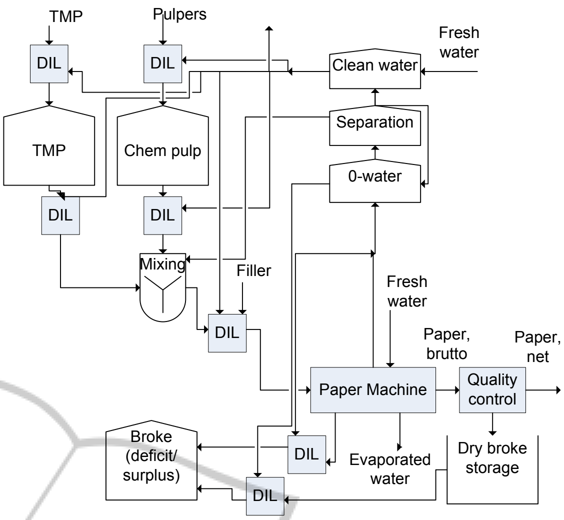


Figure 3: Flow diagram of the process in case study.

include TMP (thermo-mechanical pulp), chemical pulp, wet broke, dry broke, clean water and 0-water. The design problem is illustrated in Figure 3 and further explained in (Ropponen, Rajala, Ritala 2011).

#### 4.1.2 Stakeholders

The actors involved in the design process in the case study include the designer, optimizer and modeler. The roles were manned by research teams involved in the project.

The designer had the main responsibility of the project. He carried out the requirement elicitation with the end-customer, proposed a conceptual design and initiated the problem formulation for the optimization. He then had a key role in data acquisition for the model building. After getting the optimization results, he made the decisions according to the end-users preferences.

The optimizer participated in the problem formulation by having an opinion what kind of problems can be solved with optimization. After the problem formulation, the optimizer then asks the modeler to build necessary models for optimization and then chose the right optimization method. Finally, a suitable method for presenting the results was chosen.

The modeler was responsible for creating a model simple enough to be calculated. The modeler was also responsible to make sure that the simplifications do not affect to the problem to be solved.

### 4.1.3 Business Process

The project could be divided into four main tasks: problem formulation, model building, problem solving (optimization) and result interpretation.

**Problem Formulation**

At the starting point of the case study a part of the conceptual design was already performed, e.g. the number of storage towers and material flows between them was defined. The designer and optimizer then discussed the possibilities for a manageable optimization problem. They designed that the optimization activity concerns only about operation design and the dimensioning part of the structure design. Also the amount of optimized parameters was reduced in negotiations between the designer and the optimizer. During the optimization activity a mathematical model of the problem was created and used for finding an optimal design under the specified requirements. The design problem was formulated as follow:

$$\min_{d}\left\{\begin{array}{l}\sum_{i=1}^{4} H(V_{i,\max}) \\ E_{\psi}\left\{(q_{Filler}(n)-q_{0,Filler})^{2}\right\} \\ E_{\psi}\left\{(q_{bw}(n)-q_{0,bw})^{2}\right\} \\ E_{\psi}\left\{(q_{strength}(n))^{2}\right\} \\ E_{\psi}\left\{(u(n+1)-u(n))^{2}\right\} \\ -E_{\psi}\left\{T_{v}\right\}\end{array}\right\} \tag{2}$$

where $H(V_{i,max})$ is the investment cost of the 4 selected tower volumes, $T_V$ is the time till one of the towers goes empty or flows over, and $E_{\Psi}\{\}$ denotes the expectation value of the system performance as $\Psi$ is the stochastic process with applied dosage policy. (Ropponen, Rajala, Ritala, 2011)

The operational problem, i.e. the lower level of the BLMOO was formulated as:

$$\min_{u}\left\{\begin{array}{l}\sum_{k=1}^{K_H} \gamma(k)(q_{Filler}(n+k)-q_{0,Filler})^{2} \\ \sum_{k=1}^{K_H} \gamma(k)(qbw(n+k)-q_{0,bw})^{2} \\ \sum_{k=1}^{K_H} \gamma(k)(q_{strength}(n+k)-q_{0,strength})^{2} \\ \sum_{k=1}^{K_H} \gamma(k)(u(n+k)-u(n+k-1)^{2} \\ \max\limits_{k=1..K_H} \dfrac{p(V_i(n+k)>V_{i,\max})}{p_i^{(up)}(k)} \\ \max\limits_{k=1..K_H} \dfrac{p(V_i(n+k)>V_{i,\min})}{p_i^{(down)}(k)}\end{array}\right\} \tag{3}$$

$$s.t \quad u_{j,\min} \le u_j \le u_{j,\max}$$

where $q_{filler}$ , $q_{BW}$, and $q_{strength}$ are the quality variables with $q_0$s as their nominal values, $K_H$ is the optimization horizon, $\gamma$ *(k)* a time-wise weighting factor, $u$ is a vector of pulp/water flows to be controlled, $p_i^{(up)}(k)$ and $p_i^{(down)}(k)$ are the accepted risks for a tower overflow/goes empty $k$ time steps from the present time $n$ defined as $p_i^{(up/low)}(k) = 1-\left(1-p_i^{(up/low)}\right)^k$, $i$ refereeing to the storage towers for clean water, 0-water, broke, and dry broke. $V_{i,max}$ is the volume of the $i$th storage tower, i.e. the maximum amount of pulp/water in the tower, and $V_{i,min}$ is the minimum amount of pulp/water in the tower. U is the control variable describing the broke dosage from the broke tower to the system (Ropponen, Rajala, Ritala, 2011).

Simplified, on the operational level we optimize the variances of the quality attributes of the paper and the broke dosage and the probability of under/overflows. On the design level, we optimize the design according to the sizes of the tanks and expectation values of the system performance.

**Model Building**

At the same time that the optimizer negotiated with the designer about the problem formulation, he had to discuss with the model builder if a suitable model for the problem can be built. In this discussion there were two main themes: is the physical phenomenon of the problem known or is there enough data to model the problem stochastically and can the model be simple enough that it can be calculated fast enough in the optimization loop.

**Optimization and Result Interpretation**

In this case example, the tasks of problem formulation, model building and optimization were performed simultaneously and were highly iterative. The main focus of the case example was in optimization. The results of the optimization are described in (Ropponen et al., 2011) and (Ropponen, Rajala, Ritala, 2011).

After the optimization, the results were presented to the designer as two-dimensional Pareto optimal sets. In Fig.3, a Pareto optimal set in respect to the two most important parameters is presented. The designer then made the decisions e.g. between a decent investment cost and an acceptable probability of break.

### 4.1.4 Data, Knowledge and Models

The designer in this case had a wide experience in process design, paper making, modeling and optimization. The optimizer was mathematically oriented, but had only minor experience on paper making or process design. The modeler was familiar with process modeling and optimization.

The largest data flow in the process was from designer to optimizer. The designer had to communicate the customer requirements, the original design about the structure and operation and the freedoms and limitations for optimization in the design. The main models for this communication were a process flow sheet and steady-state model of the process. Making of these models was mainly a task for the designer. The designer was able to formulate most of the limitations and requirements in numerical form, e.g. the probability of the break may not be greater than Pmax. Due to the nature of a first time project, the data transfer between the optimizer and modeler was also huge.

Modeller was responsible for building three models: dynamic model, predictive model and a validation model. The two first mentioned were used in optimization while the validation model build with different simulation software was used only for one selected design.

Practically, the problem formulation and optimization required simultaneous model development, because there wasn't previous knowledge about feasible models.

The results of the optimization were delivered as a document containing simulation graphs and Pareto optimal sets (one example in Figure 4) of optimization results.

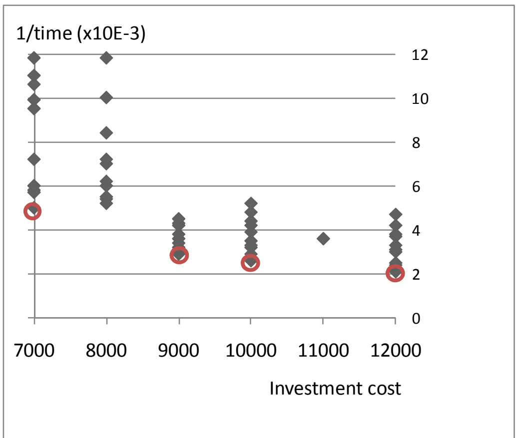


Figure 4: Design solutions in respect to investment cost and time until production stop. Pareto optimal set of designs circled. (Ropponen, Rajala and Ritala, 2011).

### 4.1.5 Information Tools

This case example was carried out as a research project, and therefore the engineering tools used didn't match the ones used in industry. MATLAB was used both for the optimization and simulation for optimization. APROS process simulator was used in validating the results of optimization.

## 4.2 Interviews

In order to get information of the process engineering business process today and to validate the proposed changed to the process in order to adopt a new optimizing design process, a set of interviews were performed. The interviewees represented actors in both chemical and pulp & paper industries and contained process designers, automation designers and IT-system experts in process design companies and engineering enterprises. In addition a simulation expert and an optimization expert were interviewed.

The topics of the interviews were motivation and feasibility of optimizing design, current design practices vs. optimizing design and IT systems vs. requirements of optimizing design.

The following observations could be made about issues concerning *the motivation and feasibility of optimizing process design:*

There are business requirements to decrease the costs of plant design projects. At the same time the quality of the design should be increased and cost decreased. The effect of optimizing process design process on all three aspects (design quality, design cost, project cost) should be taken into account.

The process design practices in different industries are heterogeneous. In paper and pulp industry process design can be characterized as engineering-oriented, i.e. an engineering design system is the primary design tool. As a comparison, in chemical industry process design is quite simulation-oriented, i.e. a simulator is the primary design tool. The design practices of chemical industry are closer to the optimizing process design process than the ones in paper and pulp industry.

The following observations could be made about issues concerning *the differences between current design practices and optimizing design*:

Cooperation between different parties involved in a design project has recently been emphasized by engineering companies. Cooperation is needed for the efficiency of a design process, e.g. finding out the requirements of the customer early enough, ensuring consistency of the designs from different designers and handling the effects of design changes. The optimizing design process should fit to the cooperation practices.

The design of a process is divided to several designers according to different systems or parts of the process. This is done due to the different expertise of the designers and concurrency of the design work. There are usually some buffers in the design between the designs by separate designers. From the optimization viewpoint this division is questionable. The optimizing design process is likely to change the division of work.

The division of work is also reflected to current optimization practices. They are optimizing unit processes rather than the whole process. The optimizing design process should change this practice, too.

The trust of the customer on the feasibility of the process design in a very important issue, which is affected by many factors, e.g. references of the vendor and difference of the design to existing ones. It was mentioned that particularly in the paper and pulp industry customers do not trust simulations as a process design validation tool. Validation of the design results should be a primary concern also in optimizing process design.

The following observations could be made about issues concerning the *differences between requirements for current IT systems and IT systems when using optimizing design*:

The IT-architecture of an engineering company is usually quite heterogeneous, i.e. there are several different IT-systems used during a design project. Sometimes there are even several alternative IT-systems for same design tasks, e.g. due to customer requests. The heterogeneity of IT-systems may hinder the implementation of IT-support optimizing design.

There is a slowly progressing shift from document-centered design paradigm to data-centered design paradigm in plant design. The optimizing process design process should be made to fit the data model -oriented design paradigm because its meaning seems to be increasing in the future. It is also likely to be more suitable basis for optimizing design than the older document-oriented design.

## 5 CONCLUSIONS

In this paper a business process model for optimizing design in continuous process facility engineering has been presented. This model was considered from the viewpoints of stakeholders, process, knowledge, data, models and tools. The model for optimizing design was then assessed by applying it in an experimental case study and by interviewing experts.

Based on this study, a few conclusions can be made. The greatest change is the new roles of optimizer and modeler, which make the process more iterative between optimizer and process designer. The new roles require a shared knowledge, because the work can be described as expert co-operation. The business process in optimizing design is more iterative than in traditional design because of the need for negotiation in the problem formulation and the uncertainties in the modeling. In addition to this, the interviews also illustrate the importance of validation of process designs. Validation of the designs so that the customer will trust them is a primary concern to be observed in future research.

It must be noted that the design business process in this paper is presented at a general level and it must be specified when used as actual process. In future, the process model is evaluated and specified in a larger case study.

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