

Multi-Objective Optimal Design of Sustainable Products and Systems under Uncertainty

by

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Abstract

Sustainable approaches have been extensively proposed in product, process and system levels. However, a lack of applicable solutions for these methods is identified in the existing research. This research considers uncertainties affecting sustainable systems and comprehensively discusses the need for optimal design in product and system levels under uncertainty.

Based on the economic, social and environmental requirements of a sustainable product, and uncertainties in engineering systems, two innovative methods are proposed. The methods, including agent-based modeling (ABM) and Big Data, quantify the effects of users' preference changes as a significant uncertainty source in a product design process. The effect of quantified uncertainties on the product sustainability is then evaluated, and solutions to reduce the effects are developed. Through a novel control engineering method, uncertainties are modeled in the design process of a product. Using two mathematical models, the cost and environmental impacts in the design process are minimized under users' preference changes. The models search for an optimal number of iterations in the design process to achieve a sustainable solution.

The proposed methods have been extended to model and optimize the sustainable system design under uncertainties. Design of Eco-Industrial Parks (EIPs) is a practical and scientific solution to achieve sustainable industries. To improve the feasibility of flow exchanges between industries in an EIP under several uncertainties, this research provides a perspective analysis for establishing flow exchanges between industries. The sources of uncertainties in

the EIPs are then comprehensively studied, and research gaps are highlighted. Finally, models to optimize flow exchanges between industries are presented and the validity of models is evaluated using real data.

One of the major contributions in this research is including all sustainability pillars in the proposed approach. The research addresses users' preferences to highlight the role of individuals in the society. Moreover, the economic and environmental objective functions have been considered for optimal decision making in the design process. This research underlines the role of uncertainty studies in sustainable system design. Multiple classifications, perspective analysis, and optimization objectives are presented to help decision makers with the optimal design of sustainable systems under uncertainties. The proposed method can support and promote sustainable design in industries using multiple objective optimized decisions.

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Dedication

To my dear parents, and my beloved wife!

Table of Contents

Abstract	I
Acknowledgements	III
Dedication	IV
Table of Contents	V
List of Tables	VIII
List of Figures	X
List of Abbreviations	XIII
Nomenclature	XV
Copyright Notices	XVIII
Chapter 1: Introduction	1
1.1 Sustainable product and system design	1
1.2 Effects of uncertainties on product and system design	3
1.3 Importance of the optimal design for sustainable products and systems under uncertainties	5
1.4 Objectives of this research	7
1.5 Contributions of the dissertation	9
1.6 Structure of the dissertation	9
Chapter 2: Literature Review	12
2.1 Change propagation approaches	13

2.2 Agent-based models	15
2.3 Big Data methods	17
2.4 Summary of methods to model and quantify effects of uncertainties on product in the design phase	18
2.5 Methods to model uncertainty and reduce its effects	20
2.6 Methods to analyze disturbances in product design	21
2.7 Modeling Eco-Industrial Parks (EIPs) as sustainable systems	26
2.8 Methods to evaluate effects of uncertainty in EIPs	31
Chapter 3: Modeling and Quantifying Uncertainty in the Product Design Phase	36
3.1 Introduction	36
3.2 Proposed methods to model and quantify uncertainty under user preference changes	39
3.2.1 Agent-based modeling for the prediction and transferring changes into the product development	39
3.2.2 Big Data analytics approach for the prediction and transferring changes into product development	46
3.3 Application of proposed methods	50
3.3.1 Application of the agent-based model	51
3.3.2 Application of Big Data Analytics (BDA)	55
3.4 Analysis and discussion	58
Chapter 4: Design Optimization for Sustainable Products under Uncertainty	64
4.1 Introduction	64
4.2 Evaluating effects of uncertainty on sustainable product design	65
4.2.1 Proposed methodology to evaluate effects of uncertainty on product design	66

4.2.2 Validation of the proposed approach	70
4.3 Optimizing sustainable product design under uncertainty	79
4.3.1 Proposed methodology to optimize sustainable product design under uncertainty	81
4.3.2 Validation of the proposed approach	92
4.3.3 Analysis and discussion	96
Chapter 5: Multi-objective design of sustainable systems under uncertainty	103
5.1 Introduction	103
5.2 Modeling symbioses in eco-industrial parks for stakeholders' perspectives	105
5.3 Multi-objective design of symbioses under uncertainty	112
5.4 Case study	115
5.4.1 Perspective analysis for modeling symbioses in EIPs	117
5.4.2 Studying the effect of uncertainty on the optimal symbioses network	120
Chapter 6: Conclusions and Recommendations for Future Work	130
6.1 Concluding remarks	131
6.2 Recommendations for future research	135
Bibliography	137
Appendix A	152

List of Tables

Table 1.1 Definitions of uncertainty in literature related to product development	3
Table 1.2 Framework of the research and sequence of chapter	10
Table 2.1 Summary of specifications for reviewed Engineering Change prediction methods	19
Table 2.2 Summary of the specifications of the methods to analyze disturbances in product design	23
Table 2.3 Summary of main industrial symbioses in EIPs	27
Table 2.4 Classification of energy exchange networks	28
Table 2.5 Summary of reviewed literature in modeling industrial symbioses in EIPs	30
Table 2.6 The framework to study uncertainties in optimization of industrial symbioses	33
Table 3.1 Summary of elements in the proposed agent-based model	45
Table 3.2 Comparison of the proposed methods in terms of technical factors, social factors, and scope of data	47
Table 3.3 The values utilized for the defined parameters in the studied smartphone	51
Table 3.4 Evaluation of interdependencies between components of the studied smartphone	54
Table 3.5 Measurement of changes transferred into each FR using linear regression equations	58
Table 3.6 Evaluated magnitude of changes (MAG) for each component using proposed methods and real changes of the smartphone	59
Table 3.7 Error measurement for the proposed methods	59
Table 3.8 Sensitivity analysis for the selected parameters in the proposed agent-based method	61

Table 4.1 List of parameters used in ABM for the wheelchair life cycle simulation	71
Table 4.2 Comparing rankings of the FRs (the proposed method versus the FIM only)	73
Table 4.3 List of the criteria to estimate design activities for DPs	77
Table 4.4 Comparing proposed method with the traditional methods to improve product environmental impacts	79
Table 4.5 The amount of work in each iteration	94
Table 4.6 The environmental impact analysis for the selected parts in iPhone using PRé Consultants (2015)	95
Table 4.7 The cost analysis for the smartphone	95
Table 4.8 The analysis of objective function values for the cost model with uncertainty ...	97
Table 4.9 The objective function values and validity test for the second model with uncertainty	99
Table 4.10 The objective function values and validity test for the second model without uncertainty	100
Table 5.1 Uncertainties identified to model for industrial symbioses optimization	113
Table 5.2 Distances (KM) between industries in the studied area	116
Table 5.3 Energy specification of industries in the studied area	116
Table 5.4 Major parameters included in the models	116
Table 5.5 Comparing two energy symbioses networks	117
Table 5.6 Efficiency measures for symbioses networks	119
Table 5.7 Uncertain parameters included in the models	120
Table 5.8 Comparing optimized symbioses networks using single and multiple objective functions	122
Table 5.9 Evaluations of indexes under the demand uncertainty	126

List of Figures

Figure 1.1 Globally averaged GHG concentrations adapted from (IPCC, 2014a)	6
Figure 1.2 Three stages of product design process	8
Figure 3.1 Schematic of the proposed agent-based model (ABM)	39
Figure 3.2 Process of agent-based modeling	41
Figure 3.3 Schematic view of elements and interactions in the proposed agent-based model	42
Figure 3.4 Summary of events affecting customer's preferences in a product life cycle	43
Figure 3.5 Proposed method to quantify changes of product using Big Data Analytics (BDA)	47
Figure 3.6 Detail transactions in Big Data Analytics	48
Figure 3.7 Exploded view of the smartphone to model changes in its life cycle (Afshari and Peng, 2015b)	50
Figure 3.8 Houses of quality in the QFD technique	51
Figure 3.9 Defined state chart for agents' interactions	52
Figure 3.10 Graphical representation of simulation steps: (a) Start-up of simulation, all agents are in blue color, (b) Technology broadcasting, technology follower agents turn to green, (c) agents accepting a friend's invitation turn to red	54
Figure 3.11 Interest over time for selected key words search "Cell Phone", Mobile Phone", and "Smartphone" using Google Trends	55
Figure 3.12 Sequence of analysis for the proposed Big Data analytics methods	56
Figure 3.13 Measured trends for FRs using a linear regression model	57

Figure 3.14 Ranking of the components using the proposed agent-based method and Big Data analytics method	61
Figure 4.1 Methodology to evaluate uncertainty effects on environmental impacts of a product	66
Figure 4.2 Environmental impacts (EI) analysis based on component weight (W) in product function of the wheelchair	75
Figure 4.3 Mapping Functional Requirements (FRs) to Design Parameters (DPs) using Axiomatic Design theory	76
Figure 4.4 Prioritizing DPs to minimize the environmental impacts according to the normalized index of budget	78
Figure 4.5 Stages of the proposed methodology for a design process under uncertainty	82
Figure 4.6 The structure of a closed-loop feedback system model based on Equation (4.14)	86
Figure 4.7 The proposed solution approach for the optimization model	91
Figure 4.8 WTM for the smartphone	92
Figure 4.9 The Apple expenses for Research and Development (R&D) (Statista, 2016) ...	96
Figure 4.10 The objective function values for the cost minimization model using (a) first cost scenario, (b) second cost scenario, and (c) third cost scenario	98
Figure 4.11 Objective function values for models including and excluding uncertainties .	101
Figure 5.1 Schematic view of a single industry	104
Figure 5.2 Schematic view of industrial symbioses	104
Figure 5.3 Industries (a) before and, (b) after energy symbioses	106
Figure 5.4 Relations between temperature and enthalpy	111
Figure 5.5 Steps for the optimal design of industrial symbioses under uncertainty	112
Figure 5.6 Map of anonymized industries to investigate possible energy symbioses	115

Figure 5.7 Energy symbioses network for (a) buyers' perspective, (b) EIP managers' perspective	117
Figure 5.8 Optimized symbioses networks using (a) the minimization of environmental impacts, (b) the minimization of the total cost, and the multi-objective model ..	121
Figure 5.9 Comparing effects of the demand uncertainty on the optimized flow exchanges in the multi-objective model	123
Figure 5.10 Comparing effects of the supply uncertainty on optimized flow exchanges in the multi-objective model	124
Figure 5.11 Comparing effects of the uncertainty in the supply prices on the optimized flow exchanges in the multi-objective model	124
Figure 5.12 Comparing the optimized flow exchanges using the stochastic and the robust models	127
Figure A.1 First QFD matrix for the smartphone	153
Figure A.2 Calculation of magnitude of changes for the smartphone	154

List of Abbreviations

ABM	Agent-Based Modeling
AD	Axiomatic Design
ANNs	Artificial Neural Networks
BDA	Big Data Analytics
BOM	Bill of Material
CI	Coupling Index
CO ₂	Carbon Dioxide
CPI	Change Propagation Index
CPM	Change Prediction Method
CPM	Critical Path Method
CTR	Carbon Tax Reduction
DA	Design Analytics
DFV	Design for Variety
DPs	Design Parameters
DS	Demand Satisfaction
DSM	Design Structure Matrix
EIP	Eco-Industrial Park
eLCC	environmental Life Cycle Costing
EOL	End Of Life
FBS	Function-Behavior-Structure
FI	Function Impact
FIM	Function Impact Method
FRs	Functional Requirements
GERT	Graphical Evaluation Review Technique

GHG	Greenhouse Gas
GVI	Generational Variety Index
HENs	Heat Exchange Networks
HoQ	House of Quality
HSS	Homogenous State-Space System
IS	Industrial Symbiosis
LCA	Life Cycle Assessment
LCT	Life Cycle Thinking
MAS	Multi-Agent Systems
MILP	Mixed Integer Linear Programing
NHSS	Non-Homogenous State-Space System
NO _x	nitrogen oxides
NPD	New Product Development
ORC	Organic Rankine Cycles
PD	Product Development
PLC	Product Life Cycle
QFD	Quality Function Deployment
SAM	Sample Average Method
SCDU	Supply Capacity under Demand Uncertainty
SD	Sustainable Development
sDSM	sensitivity Design Structure Matrix
SHIP	Supply Hub in an Industrial Park
SU	Supply Utilization
WTM	Work Transformation Matrix

Nomenclature

Chapter 3

$Y(t)$	Total number of customers who adopt new products at time t
\bar{Y}	Total number of potential adopters
m	Leading customers who buy a new product without the influence of others
n	The people who buy a new product influenced by others
I	Set of customers ($i \in I$)
J	Set of product parts and components ($j \in J$)
T	Set of time of events ($t \in P$), and ($P \in T$)
t	Index of time when people interact with each other
P	Index of time when new technology updates are advertised
$CP_{i,j}(t)$	Preference of customer i for part j at time t
$\gamma_{frd}(i, j, t)$	Adoption probability of customer i for part j at time t when interacting with a leading friend,
ω_{frd}	Weight of imitation (inspired by friends) in adopting a new technology,
P_{frd}	Technology preference of a friend,
$\varphi_{tech}(i, j, P)$	Adoption probability of customer i for part j at time P a new technology is introduced,
ω_{tech}	Weight of innovation (inspired by media) in adopting a new technology,
$R_{tech}(j)$	Rate of technology improvement for part j ,
\overline{CP}_j	Average customers' preference for part j
$P_m(t_{mn})$	Product lifetime
INT	Dependency matrix of n part
MAG	Magnitude of changes transferred to product parts from external interactions during a product life cycle
CHG	Total changes transferred into all components of a product
CHG_{real}	Real changes of the product components

Chapter 4

$\Delta FR_{S_{Uncertainty}}$	Changes of FRs
ΔFI	Changes of function impact
$[A]$	Design matrix (mapping FRs into DPs)
\tilde{r}	Rigidity of Design Sustainability
G	Index for efficient prioritizing DPs
El_i	Environmental impacts of component i
RB_i	Required budget to design component i
f	Discrete time variable to denote a finite number of iterations
$\mathcal{X}(f)$	Work vector consisting of n coupled design tasks to be completed
$\mathcal{W}(f)$	Disturbance input in iteration f due to unexpected external events
$\mathcal{U}(f)$	Additional resources that each task needs to reach the desired state
\mathcal{A}	Work transformation matrix
\mathcal{B}	Disturbance Transformation Matrix
\mathcal{C}	Proportion of common resources shared by two or more tasks
K	Feedback gain matrix
$\mathcal{C}\mathcal{I}_f$	Cost of iteration f within a design process
$\mathcal{C}\mathcal{R}_j$	Unit cost of resource j used to compensate time
U_{kfj}	Amount of resource j used within iteration f for task k
R_j	Available units from resource j in the design process
I_{max}	Maximum number of iterations
I_{opt}	Optimum number of iterations
\mathcal{P}_{kj}	Pollution of task k (e.g., CO ₂ emissions) from each unit of resource j
Z	Objective function value

Chapter 5

I	Set of supplier industries
J	Set of demand industries
K	Set of energy types

P_s	Probability of scenario s
D_j^k	Demand of industry j from energy type k
S_i^k	Supply of industry i from energy type k
L_{ij}^k	Distance of industry i and j for energy network k
U_{ij}^k	Unit cost of network between i and j for energy k
CD_j^k	Fixed cost of generating energy within industry j
CC_{ij}^k	Fixed cost of conditioning energy from industry i to j
CE_{ij}^k	Selling price of energy k from industry i to j
CI_j^k	Variable cost of generating energy within industry j
RC_{ij}^k	Cost of recovering energy k for industry j in i
TC_j^k	Tax on carbon for energy k imposed to industry j
TS_i^k	Tax saving of industry i by exporting energy k
α_{ij}^k	Depreciation rate of pipeline between i and j
β_{ij}^k	Depreciation rate of facilities between i and j
γ	Distance limit for industries to build synergies
TMP_i^k	Temperature of energy k supplied by i
TMP_j^k	Temperature of energy k demanded by j
x_{ij}^k	Percentage of demand supply from i to j for energy k
y_{ij}^k	Binary variable if symbioses exists between i and j
\dot{E}	Total heat transfer power
\dot{m}	Fluid flow rate
c_p	Heat capacity
ΔT	Temperature difference between two points
η	Fraction of supplied heat
$\mathbb{E}(f_{\theta}(x, \omega))$	Expected objective function value under uncertain parameters (v)

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Chapter 1

Introduction

1.1 Sustainable product and system design

Sustainable development (SD) requires a deep understanding of interconnected factors to meet our present needs without compromising the ability of future needs (WCED, 1987). To meeting both sustainability and development, it is necessary to integrate multidisciplinary approaches (Jabareen, 2008; Murdiyarso, 2010). Sustainable development is a dynamic process to adapt, learn, and act on interconnections among the economy, society, and natural environment called sustainability pillars (UN, 2014). An everlasting progress is impossible without a progress on all pillars simultaneously. Several methods and tools have been proposed to integrate these pillars in different disciplines for sustainability assessment purposes (Ramani et al., 2010; Sala et al., 2013a). However, it is claimed that overlaps and the complexity of challenges presented by SD are difficult to be managed using classical disciplines and methods (Sala et al., 2013b).

To achieve objectives of SD at the product level, one should consider the entire product life cycle (PLC). In the existing research on methods to apply SD, most attention has been paid to the life cycle inventory; a component of sustainability studies where a model of the product is developed to analyze its material and energy input and outputs (Assies, 1998). Methodologies based on life cycle thinking (LCT), specifically the life cycle assessment (LCA), provide a valuable support in sustainability evaluations. The LCA delivers a systematic evaluation of environmental performance in product development, from the raw material to final waste disposal (cradle to grave). The strengths of LCA are its system thinking mechanism and the interdisciplinary approach. By system thinking, the linkages and interactions of components in a system are analyzed (e.g., analysis of inputs, processes, and outputs). Using the interdisciplinary approach, impacts of a product/process are assessed. Besides the discussed advantages, methodologies based on the LCA still need to be improved to include the environmental life cycle costing (eLCC) and social life cycle assessment (Kloepffer, 2008; Sala et al. 2012).

A comprehensive evaluation of trends in sustainability analysis highlighted the need for covering the social and economic aspects in the LCA (Guinée et al., 2010). The evaluation showed that the future trend in life cycle sustainability analysis extends the scope of current LCA from mostly environmental impacts to covering all three pillars of sustainability. Moreover, the scope of analysis should be extended from the predominantly product-related level to the sector level or even economy-wide level. Thus, a desired method for SD should address the sustainability pillars all together in the product and system levels.

1.2 Effects of uncertainties on product and system design

The term “uncertainty” has been defined and discussed in many studies to fit the best meaning of research contents. In the research on product development (PD) and engineering system design, definitions for uncertainty are listed in Table 1.1.

Table 1.1 Definitions of uncertainty in literature related to product development

No.	Definition of uncertainty	Source
1	The inability to determine the true state of affairs of a system	McManus and Hastings (2005)
2	Things that are not known, or known only imprecisely	Sage (2015)
3	The difference between the information required to accomplish a task and the information currently residing with the actor charged with performing it	Suss and Thompson (2012)
4	Lack of definition, lack of knowledge and lack of trust in knowledge	Wynn et al. (2011); Afshari and Peng (2015b)

In the PD research, uncertainties are classified with different perspectives. One of the common classifications is to divide uncertainty into Aleatoric and Epistemic (Engelhardt et al., 2011; Saravi et al., 2011). The aleatoric uncertainty stems from the stochastic effects such as the random noise and measurement error. Aleatoric uncertainty is quantifiable through stochastic terms and the probability theory (Eifler et al., 2010). A challenge with the aleatoric uncertainty is that we cannot mitigate it by additional data or analysis. On the other hand, an epistemic uncertainty refers to a lack of knowledge or information. Errors in simulating processes, data collections or human errors are reasons for this type of uncertainty. In fact, increasing the precision of information can help reducing the epistemic uncertainty (Anderi et al., 2010).

Uncertainties are also classified based on available knowledge and information for an uncertain product or process. The categories are stochastic uncertainty, estimated uncertainty and unknown uncertainty (Engelhardt et al., 2011). In unknown uncertainty, both the effect and resulting deviation of a regarded property of uncertain processes are unknown. This happens in the early stages of design where the available information about the product is not enough. In the case of estimated uncertainty, effects of a regarded uncertain property are known, but the probability distribution of the resulting deviation is partially known. This may happen when the property of a product is analyzed randomly, or information about expected features of a product is not complete. Finally, in the case of the stochastic uncertainty, effects and resulting deviations of a regarded uncertain property are sufficiently explained by probability distributions. This type of uncertainty is presented after an extensive analysis and quantification of properties by experiments and analysis.

There are two types of variety in product development (Martin and Ishii; 2002); the variety within the current product being designed (spatial), and the variety across the future generation of a product (generational). The spatial variety affects product design during product development (PD) while the generational variety is witnessed after the PD. In this research, the focus is on methods and solutions for the generational variety and its effects on the product/process design.

Most engineering systems operate in uncertain environments; uncertainties require the flexibility to avoid a brittle system. Changeability is introduced as a system's ability to respond to changes with flexibility and adaptability (Ross and Hastings; 2006). Flexibility can be used to maintain the performance of systems where contextual changes occur. Hence,

the key question in product/process design is where and how to embed flexibility. A prerequisite to embed flexibility is to recognize functions and components of a product/system that are more likely to change under uncertainty. Design parameters related to the highlighted functions can be decided afterward.

Uncertainty has adverse effects on system performance at different levels. For example, Pastor and Veronesi proved that uncertainty in economic policies is negatively correlated with industrial production and economic growth (Pástor and Veronesi; 2013). In the firm level, such uncertainty could tend to decrease a company's investment decisions (Kang et al., 2014). In the supply chain level, uncertainties (e.g., demand and prices) could affect the short-term and long-term feasibility of networks (Afshari et al., 2014a; Afshari et al., 2016). A minimum effect of uncertainties on the product level is a lack of inventory to satisfy customers' demand (Bijvank and Vis; 2011). Studies show that only 15% of customers who observed a stock-out would wait for replenishment; the other 85% will leave to buy from other resources (Gruen et al., 2002). Such effects show the importance of applying appropriate strategies to deal with uncertainties in different levels.

1.3 Importance of the optimal design of sustainable products and systems under uncertainty

Reducing emission effects is essential to achieve sustainable development. Figure 1.1 depicts the globally averaged GHG emissions from 1850 to 2015 (IPCC, 2014a), which shows a significant increase in CO₂ emissions. Studies prove that long-term global warming and climate change are mainly driven by CO₂ emissions (IPCC, 2014a). Thus, strategies and action plans are required for substantial emissions reductions over the next decades. To

implement such reduction plans, technological, economic, social, and institutional challenges should be undertaken in the production sector. Industries contributed to at least 21% of global greenhouse gas (GHG) emissions in 2010 (UNGC, 2015).

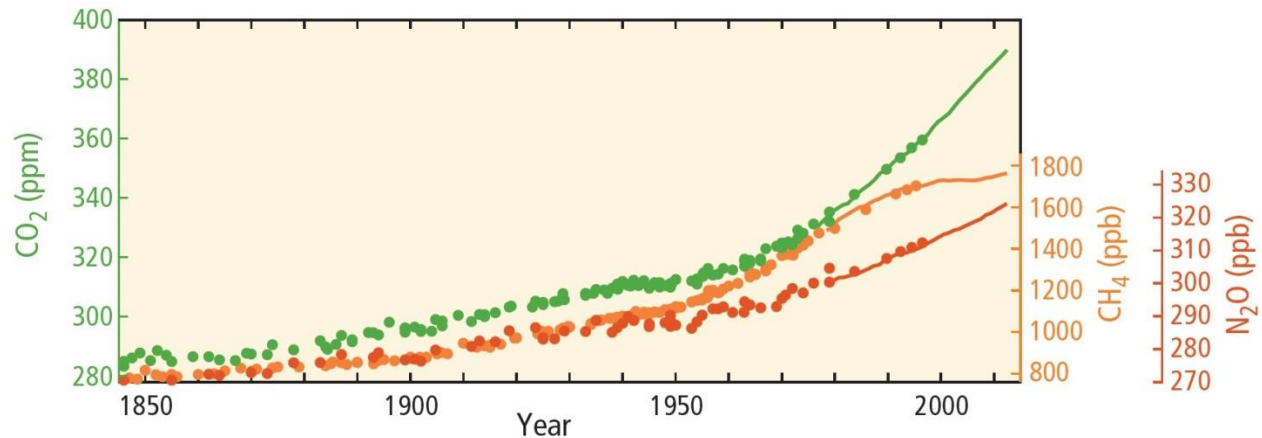


Figure 1.1 Globally averaged GHG concentrations adapted from (IPCC, 2014a)

It has been proven that decisions made in the early design phase would influence 80-90% of a product life cycle in its sustainability performance (May et al., 2011); therefore, the design phase of a product/process plays a major role in achieving sustainability goals during the product life cycle. In this regard, if a designer could identify future changes of a product in the design phase, effects of the uncertainty on environmental impacts of the product can be reduced. Nevertheless, a review of the existing research, as presented in chapter 2, identifies that methods to model and quantify uncertainty are required to be developed to deliver a reliable measurement of uncertainty.

In the system level, some manufacturing processes may end up with excessive materials, energy, water, and by-products. Although they are considered as wasted/unused resources, other manufacturers may require these resources as input for processes. Such reuse of wasted/unused resources delivers savings in terms of cost and environmental impacts. For

example, in cement or metal casting industries, the temperature of processes can reach up to 2000 ° C. Retrieving the energy available at the end of these processes can supply the required heating, steam, or energy in other nearby processes. Designing a network of exchanges of wasted/unused resources is a novel approach to reach the sustainable development goals. However, several factors such as uncertainties should be deliberated in the design process.

In summary, for the perceived need of reducing industries' share in the total GHGs, efforts should be focused on the design phase of a system. Because of a lack in the method to quantify uncertainties, new methods should be developed purposefully in the design phase. In particular, the efforts should minimize the total CO₂ emissions during the product/process life cycle using innovative approaches.

1.4 Objectives of this research

Dym and Little (2009) provided a definition of the design process as depicted in Figure 1.2. Based on this process, after the investigation of customers' requirements, customers' needs are transformed into product specifications to generate concepts of product. In the preliminary design, some details including shapes, sizes and materials are considered to solidify the final choice of design concepts. In the detail design, the preliminary design is refined and concluded in details for specifications. After the design optimization, the final design is documented for manufacturing. Thus, this research aims to find a sustainable solution at the detail design for product.

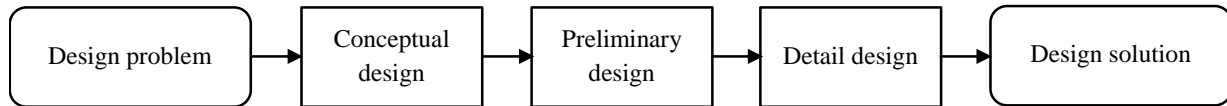


Figure 1.2 Three stages of product design process (Dym and Little, 2009)

The goal of this research is to develop optimal methods for the sustainable design of products/processes under uncertainty with the following objectives:

- Propose methods to model and quantify the effects of users' preference changes on the design of sustainable products;
- Minimize the effects of the quantified uncertainty on time, cost, and environmental impacts of sustainable products in the design phase; and
- Develop methods to the optimal design of sustainable systems with multiple objectives.

To achieve the objectives, several methods and approaches are used including: agent-based method (ABM), Big Data, axiomatic design (AD), quality function deployment (QFD), and mathematical programming. This research focuses on the design phase of a sustainable product/process. Among various uncertainties discussed in the research, users' preference changes are studied in the product design level, and the demand uncertainty of customers is applied in the process design level.

By implementing the proposed methods, it is expected that the proposed methods will help decision makers in optimizing the product/process design under the discussed uncertainties. The methods will also minimize undesired effects of uncertainty on stakeholders' objectives in the product/process life cycle.

1.5 Contributions of the dissertation

This research bridges gaps in the existing studies as listed in the following:

- Two innovative methods (based on agent-based modeling and Big Data analytics) are proposed to accurately quantify the uncertainty in users' preference changes.
- As a major contribution, all sustainability pillars are involved in the proposed approaches for each level. Please see Table 1.1 for details.
- Methods to minimize effects of the uncertainty are proposed in product, process, and system levels.
- Deterministic and stochastic models to optimize energy symbioses are presented to minimize the total cost and environmental impacts of industrial symbioses.
- Technical and economic measures are embedded in the models to identify the most resilient flow exchanges under uncertainty.

1.6 Structure of the dissertation

This dissertation consists of six chapters. Chapter 1 introduces the research background, and highlights the importance of the research, objectives, and research deliverables.

Chapter 2 reviews the existing research for modeling uncertainty and optimizing design objectives under uncertainty. Methods for modeling eco-industrial parks (EIPs) as sustainable systems are discussed using the perspective analysis. The modeling approaches are then discussed for the uncertainty analysis. The chapter is concluded with advantages, limitations, and research gap.

Table 1.2 Framework of the research and sequence of chapters

		Chapter 3	Chapter 4	Chapter 5	
Levels	Social	Economic	Environmental	Uncertainty	Method to deal with uncertainty
Product	Customers' preferences	Cost Rigidity Index	PLC emissions	Users' preferences changes	Axiomatic Design
Process	Customers' preferences	Cost minimization	Environmental Impacts minimization	Users' preferences changes	Control Engineering
System	Demand / Supply	Cost minimization	Environmental Impacts minimization	Tax on Carbon Energy prices Demand supply	Stochastic / Robust Optimization

Table 1.2 presents the framework of the research. Chapter 3 presents two proposed approaches (agent-based modeling and Big Data approach) to model users' preference uncertainty. The methods are validated using a case study. The assessed changes measured by the proposed methods are compared with real changes of the studied product to evaluate the efficiency of the proposed methods.

In Chapter 4, a method is presented to minimize the impacts of the uncertainty on the design of a sustainable product. The method uses the quantified uncertainty to evaluate its effects on a product design during the product life cycle. Using an innovative approach, control engineering and mathematical programming are combined to optimize such uncertainty effects on product design time and environmental impacts.

Chapter 5 extends the scope of research from a sustainable product to a sustainable system design. Two multi-objective optimization models are proposed to evaluate stakeholders' perspective on optimal flow exchanges in an EIP. By applying the uncertainty

analysis, the proposed models have been used to optimize the flow exchanges in the EIP under uncertainty.

Chapter 6 summarizes findings of this research and outlines possible extensions for further studies.

Chapter 2

Literature Review

The existing research on modeling, evaluating, and optimizing effects of uncertainty in the product design process is reviewed in the following sections. Discussions are presented in the product design level and system level.

In the product design level, methods to quantify uncertainties are classified into three categories including change propagation approaches, agent-based models, and Big Data methods. As a summary, the methods are compared to highlight advantages and disadvantages of the reviewed methods. The research background for the methods to reduce effects of the uncertainties is then discussed to identify the best methods to model and reduce effects of the quantified uncertainties. A detailed discussion of the method to investigate disturbances on the product design process is also presented, and research gaps are highlighted.

In the system level, methods to model eco-industrial parks (EIPs) as sustainable systems are reviewed. Uncertainties affecting EIPs are then classified in detail to identify research gaps.

2.1 Change propagation approaches

Product changes are uncertainties considered as important issues in product design (Eppinger and Ulrich, 1995; Pahl and Beitz, 2013). Methods have been proposed to model and evaluate the effects of product changes. Initially, these approaches were proposed only to measure changes in product applications (Marca and McGowan, 1987; Belhe and Kusiak, 1995). These methods were then extended to integrate the change quantification within the product development process as discussed in this section.

The design structure matrix (DSM) is a method to efficiently represent elements of a system and their interactions (Steward, 1981). The primary DSM approach organizes complex development projects by determining a sensible sequence of tasks being modeled (Yassine and Braha; 2003). The DSM captures the existence and strength of an interaction of design tasks or parts of a product (Eppinger and Browning; 2012). Several extensions of the DSM have been proposed to determine the design priority and to minimize redesign time and iterations in concurrent engineering (Yassine and Braha, 2003; Yassine et al., 2008). Wei et al. (2001) proposed a component-based DSM method to arrange high interactive components of a product in clusters. Luh et al. proposed a method to develop multiple products for different markets based on a quantified DSM (Luh et al., 2011). Using informational structure perspective, design priorities are optimized to manage the product variety. Yang et al. (2014) developed an overlapping-based DSM to measure the interaction strength for clustering components in product development projects. Evolution DSM and sensitivity DSM measure

the strength of interactions of teams performing overlapped activities. Despite the extensive application of DSM in product design, the external uncertainty is not modeled in existing methods.

Change propagation approaches study the effects of contextual changes on the internal structure and components of a product (Eckert et al, 2004). Design for Variety (DFV) methodology finds the possible changes of product needs or customers' preferences and helps designers to reduce the impact of variety on the life-cycle costs of a product (Martin and Ishii; 2002). The method quantifies the magnitude of changes in components of a product to meet the future market requirements using Generational Variety Index (GVI). Coupling Index (CI) is then used to measure internal effects of the change propagation into other product components. Suh et al. proposed Change Propagation Index (CPI) to measure the total changes propagating out of components minus changes coming into the components (Suh et al., 2007). Sensitivity design structure matrix (sDSM), introduced by Kalligeros, identifies design variables with the most sensitivity to changes; a designer could insert flexibility to these highlighted subsystems or components (Kalligeros, 2006). Giffin et al. (2009) suggested a normalized CPI to compare sensitive components in each design scenario. However, the approach lacks definition of the magnitude of changes in the multi-domain analysis.

Change prediction method (CPM), developed by Clarkson et al. (2004), measures the risk of change propagation between components using DSM. The output of CPM is a DSM including values for combined (direct and indirect) risks of the change propagation. Ariyo et al. (2008) improved the CPM by proposing a hierarchical aggregation method. The method could predict the risk across multiple levels including components, systems, and product. Koh et al. (2012) presented a model to predict and manage the undesired engineering change

propagation during the development of a complex product. House of quality and the CPM are the basis of the proposed method. The method can assess change options during engineering changes. Hamraz et al. (2013a) proposed a matrix-based algorithm to facilitate model's calculations with spreadsheet programs. The suggested technique accounts for multiple changes at a time. Several developments have been presented to the basic CPM (Hamraz et al., 2012; Hamraz et al., 2013b; Ahmad et al., 2013) to enrich the method with a better prediction and change propagation measurements. The most recent extension links the CPM with a function-behavior-structure (FBS) linkage method (Hamraz and Clarkson, 2015). The method provides details in modeling and analysis of engineering changes.

2.2 Agent-based models

Agent-based models (ABMs) or multi-agent systems (MAS) provide an effective approach to solve problems with a large size of the domain and frequently changing structure (Barbati et al., 2012). An ABM consists of a set of elements (agents) characterized by some attributes that interact with each other through defined rules in a given environment (Afshari et al., 2014b). Reviewing ABMs, there are limited applications in design fields compared to other areas. ABMs are mainly developed in the modular and collaborative design of products (Liu et al., 2014). The purpose of collaborative design is to meet customers' requirements using the collaboration of researchers from different disciplines. Multi-agent systems provide a structure to contribute designers' ideas in a collaborative fashion. Ostrosi et al. (2012) applied agent-based modeling to model product families in the conceptual design. The proposed approach envisions the configuration of product as a structural and collaborative design problem; different actors can be included in agent-based modeling. The final output of the model is a set of optimal product configurations. Cao et al. (2008) proposed an agent-based approach for the

conceptual design of mechanical products. The approach applied an agent-based structure to map behavioral and functional matrixes. A design flow proposed by Xu et al. (2008) customized products using the similarity evaluation. This method combines the analysis of customer's requirements using QFD with MAS to optimize decisions. Zhang et al. (2005) proposed an agent-based method to analyze assembly methods and assembly sequence of components. Rai and Allada (2003) proposed a two-step approach for modular product family design. A multi-objective optimization using the multi-agent framework first determines an optimized set of modules. A post-optimization then analyzes the quality loss function of each module. Other research in applications of ABM for robust product design mostly focused on collaborative solutions (Huang et al., 2000; Liang and Huang, 2002; Jia et al., 2004; Chen et al., 2014). Maisenbacher et al., (2014) applied agent-based modeling to support the product-service system development. The research highlighted the dynamic structure of the simulation within ABM to enable the uncertainty analysis. Thus, ABM has great potential to help designers model uncertainty in product development.

2.3 Big Data methods

Applications of data-centric approaches such as Big Data and business analytics have tremendously increased recently (LaValle et al., 2011; Chen et al., 2012; Buhl et al., 2013). Pattern recognition, machine learning, data mining, and Big Data analytics are tools and approaches widely used in industries and organizations. Big Data improves deficiency of other methods to quantify external and internal uncertainties in the product design process. In other words, Big Data analytics uses real data instead of predicted or simulated data as in other methods. Big Data is a buzzword used in academia and industries recently. The application of the Big Data is growing for the better data driven decision making (Obitko et al., 2013). Big

Data provides a cost-effective way to obtain users' information for a knowledge economy. As a result of the age of information, a lot of user and product data are available in the Internet for analysis of the interaction between users and producers. To obtain the advantages of data-centric approaches, organizations require a good understanding of how the methods should be utilized in different decision process contexts (Davenport, 2012; Işık et al., 2013). The study by Tien (2013) recommends four steps or components for Big Data processing including: acquisition (data capturing), access (data indexing, storing, sharing, and achieving), analytics (data analysis and manipulation, and application (data publication). Huge popularity and applications of social networks have motivated companies to focus on social or commerce mining. Analysis of the customer behavior, opinion mining, user relationship mining and clustering, and sales prediction is a growing research in industries (Chon et al., 2006; Al-Noukari and Al-Hussan, 2008; Cohen et al., 2009; Provost and Fawcett, 2013). Some applications include using customer relationship mining to formulate proper strategies for managing customer demands (Lam et al., 2014), and the online opinion analytical framework to detect weaknesses of a product (Wang and Wang, 2014). Social network mining has shown great potentials as a valuable source for Big Data analytics (Song et al., 2014). The study showed that if a user's opinion were stated in online space, the preferences of customers in the market would be affected.

Despite the benefits and potentials of using Big Data, limited studies were found to apply Big Data analytics for the uncertainty quantification in product lifetime. Dutta and Bose (2015) proposed a framework to implement Big Data projects in manufacturing. The framework consists of three main stages including strategic ground work, data analytics, and implementation. An application of the proposed framework in a cement manufacturing

corporation showed that a clear understanding of the problem, management support, cross-functional teams, and culture of data-driven decision making are necessary for the success of Big Data projects. Van Horn et al. (2012) reviewed the methods and applications to use Big Data in early, middle, and late stages of the product design phase. They proposed Design Analytics (DA) as a paradigm to transform customer data into design knowledge. The DA includes capturing, storing, and leveraging digital information about a product and its performance and usage. The model was used to improve the performance of a product. Other methods proposed for big data analytics in the product life cycle (Cooper et al., 2013; Rohleder et al., 2013) lack applications.

Within factory and industrial environments, machine-generated data are used for predictive manufacturing systems. Therefore, machines and systems are enabled with “self-aware” capabilities such as predictive maintenance systems (Lee et al., 2013). Considering limitations in the research for applying reliability concepts in Big Data analytics (Lee et al., 2014; Meeker and Hong, 2014), it was suggested to improve reliability and minimize uncertainty in Big Data applications for the entire product life cycle as the future research.

2.4 Summary of methods to model and quantify effects of uncertainties on product in the design phase

The literature in predicting changes during the product life cycle and transferring the changes into the product development process is summarized in Table 2.1. Ten criteria are considered to evaluate the literature. These criteria are based on requirements in change prediction modeling addressed in the literature. Considering a “change prediction method” as a system, we divide criteria into input, process, and output to highlight the literature gaps.

DSM-based methods and CPM-based methods have problems in the lack of integrating the change prediction within change modeling methods. In other words, these methods mostly evaluate the internal effects of changes in the model, while external changes are qualitatively considered. Therefore, integrated methods to predict and to evaluate changes are required. Reviewed ABM methods and Big Data based methods have shown the better compatibility with defined criteria. However, a comprehensive model is needed to meet all the criteria.

Table 2.1 Summary of specifications for reviewed Engineering Change prediction methods

Criteria	DSM ^a based Methods		CPM ^b based Methods		Agent-based Models		Big Data based Models	
	Basic model	Extensions	Basic model	Extensions	Literature	This research	Literature	This research
Input	- Integrated measurement of external uncertainty	✓				✓		✓
	- Considering variety of values & magnitudes of changes			✓	✓	✓		✓
	- Objective input parameters			✓	✓	✓	✓	✓
	- Evaluating sociotechnical uncertainty & events				✓	✓		✓
Process	- Considering dependencies between components	✓	✓			✓		✓
	- Dynamic method to update effects of changes			✓	✓	✓	✓	✓
	- Evaluating changes in various periods of PLC ^c					✓	✓	✓
Output	- Transferring uncertainty into components, functions, and DPs ^d		✓		✓	✓		✓
	- Ability of implementing on redesign process	✓	✓		✓	✓		✓
	- Ranking of design alternatives			✓	✓	✓	✓	✓
Advantages	Easy implementation		Quantifying components dependencies		Prediction of external changes		Accurate evaluation of changes	
Disadvantages	Weak to evaluate multiple changes		Weak to evaluate external changes		Dependence on developed model parameters		Limitation to access data	

Notes: DSM^a, Design Structure Matrix; CPM^b, Change Propagation Method; PLC^c, Product Life Cycle; DPs^d, Design Parameters

✓ in this table shows the existence of defined criteria for each method. Thus, it is a 0-1 table and ✓ represents 1

2.5 Methods to model uncertainty and reduce its effects

Simulation-based approaches and agent-based models are widely applied for reducing uncertainty effects in the product life cycle (Afshari and Peng, 2014). The ability of testing different improvement scenarios makes these methods popular. These methods however are limited by the needed details in individual design stages and users' behavior during the life cycle assessment. Moreover, a mistake-proof solution for product design is not guaranteed. In other words, retroactive improvement scenarios used in these methods may not be effective for unexpected uncertainties.

Another approach is using the axiomatic design (AD) theory in the product development process (Suh, 2001). Two axioms including independence axiom and information axiom are defined in the AD. The AD maps customers' attributes into functional requirements in the customer domain, and then functional requirements into design parameters in the physical domain, and finally, design parameters into process variables in the process domain.

Suh (2005) applied the AD to reduce or eliminate the complexity of designs via satisfying the functional requirements of products, processes, and systems based on constraints. Complexity is defined as a measure of uncertainty in achieving specified functional requirements (FRs). A solution using the AD was to reduce or eliminate information uncertainty for each type of complexity. Xiao and Cheng (2008) investigated the relationship of two axioms and robust design to conclude an inherent connection between them. Their study shows that the design satisfying independence and information axioms is more robust than other design. This proves the consistency between the AD and robust design. Kulak et al. (2010) reviewed the applications of axiomatic design, and showed that the AD is flexible in

combination with other methods and tools. None of the reviewed studies provided a solution for sustainable product development.

Kim et al. (2014) proposed a new product assessment approach to find the volume of products based on technology changes and environmental impacts of products. The approach applied AD as a function of product features to determine drivers of economic and environmental impacts. The strength of the method is the joint study of economic and environmental impacts of each product generation on the product life cycle. It lacks the study of uncertainty on product life cycle decisions. Beng and Omar (2014) proposed a framework for the sustainable product realization to facilitate developing products with less environmental harms. Axiomatic design principles were used in three areas including design for the sustainable end of life (EOL), green supplier selection, and optimization for sustainable manufacturing. The environmental effects were minimized by defining a proper relationship between FRs and DPs, and by minimizing information content of each alternative. A lack of uncertainty studying on environmental impacts during the product life cycle is witnessed.

In summary, limited research has been found in using the AD theory for the effects of the uncertainty on the product sustainability. There is an opportunity to use the AD to minimize effects of uncertainty by satisfying independence axiom and information axiom.

2.6 Methods to analyze disturbances in product design

The literature on analyzing disturbances in product design is reviewed in Table 2.2. In this table, research in internal and external sources of uncertainties and disturbances is categorized into three levels. Some papers only assessed effects of disturbances on coupled design tasks and the product development process. The other group proposed or applied methods to control

effects of such uncertainty. Some papers focused on solutions for optimizing objectives (e.g., product development time, design costs) under uncertainty. Moreover, the proposed solution approaches are classified into using control engineering principles, heuristic methods, and mathematical modeling.

Smith and Eppinger (1997) discussed a method to identify controlling features of a coupled design task in large engineering projects. The method is an extension of Design Structure Matrix (DSM) called Work Transformation Matrix (WTM) that can predict slow and rapid convergence rates within a project. Although the proposed method only identifies the coupled design features, several extended models have used its basis in the literature.

Ong et al. (2003) proposed the concept of homogenous state-space representation of design to assess effects of iterations on product development time. The proposed method was compared with the WTM (Smith and Eppinger, 1997). It is concluded that the eigenvector of state-space representation can be used as in the WTM to identify the controlling features of coupled design tasks. The paper referred to potentials of the state-space representation to minimize the duration of a product design process even before any task begun.

Lee et al. (2004) proposed a generalized homogenous and non-homogenous concept to analyze and control the stability and convergence rate of coupled design tasks. Because the proposed non-homogenous model considers extra resources for each design task per iteration, effects of the disturbances are controlled to reach desired design time. A heuristic solution based on control engineering theory was developed to measure a gain matrix of the proposed state feedback control. However, the paper lacks in using an optimization model to decide the best number of iterations with uncertainties.

Table 2.2 Summary of the specifications of the methods to analyze disturbances in product design

Author(s)	Disturbance Analysis Level			Objective(s)			Solution Approach		
	Assess	Control	Optimize	Time	Cost	Other	Control Engineering	Heuristic	Mathematical Modeling
Smith and Eppinger (1997)	✓			✓			✓		
Ong et al. (2003)	✓			✓			✓		
Lee et al. (2004)		✓		✓			✓	✓	
Huang and Chen (2006)		✓		✓				✓	
Kim (2007)	✓			✓			✓		
Chen and Ju (2010)			✓	✓			✓	✓	
Platanitis et al. (2010)	✓			✓			✓		
Xiao et al. (2011)		✓		✓			✓	✓	
Leon et al. (2013)		✓		✓	✓		✓	✓	
Chen and Xiao (2014)			✓	✓	✓			✓	
This research			✓	✓	✓	✓	✓		✓

Huang and Chen (2006) presented a method to estimate the project completion time for engineering project management. Using a simulation based approach, factors affecting the project completion time in dynamic environments were investigated. It is proved that the DSM method could overcome limitations of the traditional Program Evaluation Review Technique (PERT) and Critical Path Method (CPM) that cannot handle the task rework/iteration.

Kim (2007) extended previous research by suggesting a framework to analyze the dynamics of design iterations. The framework applied control techniques in its analysis to accurately predict the required number of design iterations even before the design process initiates. Platanitis et al. (2010) extended the homogenous state-space representation and WTM methods to include unexpected disturbances in the design process. The proposed method can evaluate effects of the disturbances per iteration of the design process by precise measurements of increased design lead-time. Using a concept of design rigidity, the amount of rework imposed by unexpected disturbances was measured in terms of excessive iterations. The method lacks in controlling such disturbance to reach the pre-defined design lead-time.

Chen and Ju (2010) investigated methods to minimize the design iteration time. A method to modify the time and the number of iterations was proposed to minimize the total product development time. To determine the time required per iteration, learning the effects of a design task are considered in the proposed model as well as the degree of dependency between in the design tasks. Xiao et al. (2011) evaluated effects of some uncertain factors on the coupled design tasks. They investigated task durations, output branches of tasks, and resource allocations as uncertainties in the product design process in a dynamic environment. A fuzzy-based feedback control approach was proposed to monitor and control these uncertainties by

introducing the resource-regulating matrix. The method improved the stability and the convergence rate of product development tasks in a dynamic environment.

Leon et al. (2013) presented an analytical framework for the efficient management of projects with uncertain iterations. Using the DSM and GERT, iterative process architectures are improved, and the project performance is predicted. Despite the useful framework proposed for New Product Development (NPD) projects, the research should be extended to optimize the framework for the iteration management. Chen and Xiao (2014) reviewed the existing shortcoming of the WTM model to propose a combination of the tearing approach and inner iteration methods for complementing the WTM model. In addition, the research introduced an algorithm for optimal decoupling schemes. However, the research left the decision for the best number of iterations to designers.

In summary, most of the existing research has focused on assessing and controlling the effects of internal and external disturbances on the coupled design tasks during the product development process. There is a lack of research to optimize objectives of product development costs, sustainability, quality, etc. under uncertainty. Although the optimization methods such as operations research have shown a great potential in optimization problems, no research has been found for the optimal lead-time of coupled tasks in product design. Therefore, this research proposes a combination of control engineering theory and mathematical modeling for the multi-objective optimization of coupled design tasks in the product development.

2.7 Modeling Eco-Industrial Parks (EIPs) as sustainable systems

As described in the introduction chapter, the aim of establishing an EIP is to utilize the competitive advantage in collaborations and the synergies (physical exchange of materials, energy, water, and by-products) stemming from geographic proximity (Chertow, 2000). Despite numerous research on material exchanges (e.g., water treatment) in EIPs, there is a modest number of publications dealing with the energy exchange between units, and even lesser on thermal energy networks. Research by Fichtner et al. highlights fundamental differences between energy exchange symbioses and other types of networks (2004). First, the energy (such as electricity and heat) is hard to store; the balance between supply and demand is required. Second, establishing energy exchange networks requires huge investments (e.g., heat exchangers, pipes). Third, industries involved in the symbioses should be close enough to avoid energy losses in pipes and networks (Korhonen, 2001). Therefore, proposing an optimal framework for the optimal design of energy exchange networks is challenging.

In the literature, symbioses have been generally described in two main models: the planned EIP model and self-organizing symbiosis model (Chertow, 2007). Other industrial symbioses with a mix form are also reported (Van Beers and Biswas, 2008). A common attribute of all models is that the symbioses should be economically feasible (Boix et al., 2015). In addition, the planned EIPs were initially designed to satisfy other objectives such as environmental friendly goals as reported in China. In this case, third parties such as government are involved in the establishment of planned EIPs. The self-organized symbioses form individual negotiations between industries to achieve business goals by the exchange of resources. Table 2.3 summarizes features used to classify industrial symbioses.

Table 2.3 Summary of main industrial symbioses in EIPs

Type	Deployment Approach	Objective(s)	Focus on	Example
Self-organized	Bottom-up	Mostly business goals	Existing industries	Kalundborg, Denmark (Domenech and Davies, 2011)
Planned	Top-down	Economic, social, and environmental	Mostly new industries	Ulsan, South Korea (Behera et al., 2012)

The early synergies concerned only the material exchange, which has three main challenges before building a symbiosis:

- Industrial units need energy for the thermodynamic consumption of processes, provided through utilities such as heating, cooling, and electricity (Hipólito-Valencia et al., 2014). Uncertainties in fuel prices and investment costs could increase the concerns. In a synergetic relation, the energy coming from recovered heat is cheaper than onsite generated energy.
- Reusing or recovering wasted heat not only can minimize the total cost of industries, but also can provide some economic benefits for internal or external use. In most cases, the infrastructure cost for exchanging the recovered energy is worth investing from the suppliers' point of view.
- Environmental concerns should be considered when modifying requirements for industrial utilities, because wastes discharged from the utility networks are restricted by environmental regulations (Kim et al., 2010). Penalties such as tax on carbon are subject to increase.

It is useful to classify energy exchange networks based on sources of supply. Some networks use the inter-firm energy waste to supply their energy demand (type A). Obviously, the supply power will be limited to the existing wasted energy after a recovery process. In

another type, a set of energy hubs is established to supply energy needs of partners (type B). An example is using incinerators fed by wastes to supply energy. In type C, industries share wasted/unused energy in their processes with other fitted partners. Table 2.4 reviews classified energy networks according to selected criteria. In terms of EIP, energy network type C can provide more energy symbioses among units. In fact, discussed symbiosis type C can partly replace energy generated by fossil fuels, which means that environmental impacts would be significantly reduced.

Table 2.4 Classification of energy exchange networks

Criteria	Type A	Type B	Type C
Investment cost	Min		
Supply power		Max	
Shutdown risk		Max	
Energy waste reduction		Min	
Industry to industry connection			Max
Buyers' negotiation power			Max
Environmental impact reduction			Max
Domain	Internal	External	External
Optimal decision(s)	-Internal recovery network	-Hub location -Network	-Partners

The existing literature shows that Pinch analysis and mathematical programming are major approaches in optimizing energy sharing networks in EIP. The Pinch point analysis is introduced as a systematic process design methodology that ensures an optimal use of energy. A minimum temperature difference ΔT_{min} between hot and cold streams characterizes the pinch and designates the location where the heat recovery is the greatest constraint (Chapter 10, 2003). Many studies have investigated total site heat integration using Pinch analysis

(Karimkashi and Amidpour, 2012; Varbanov et al., 2012; Liew et al., 2013; Liew et al., 2014a; Liew et al., 2014b). However, Boix et al. (2015) discussed that “energy balances require an exact resolution through a Mixed Integer Linear Programming (MILP) or Linear Programming (LP) which makes mathematical programming the only approach available to solve the problem” (Boix et al., 2015). They also claimed that an energy network between different firms is more often managed and designed but barely optimized. The main reasons are the specifications of energy sharing networks as reviewed before, and the difficulty in acquiring reliable data from plants within the EIP.

Since decisions in optimizing energy symbioses networks are to select the best set of energy flows, MILP is the dominant approach in the literature. Table 2.5 summarizes reviewed papers to optimize energy sharing networks. In the table, some attributes are used to classify the studies. The perspective analysis decides if both energy suppliers and buyers are included in the optimization (EIP perspective) or the analysis is conducted separately (individual based). The type of energy sharing networks as well categorizes the studies. Technical constraints, optimization objectives, and solution approaches are investigated in Table 2.5.

Table 2.5 Summary of reviewed literature in modeling industrial symbioses in EIPs

Author(s)	Network Type	Type of Objective(s)	Technical feature(s)			Perspective(s)		Solution		Data	
			Temperature	Distance	Others	Individuals	EIP	Exact	Heuristic	Real	Assumed
Chae et al. (2010)	C	Min Cost	✓	✓			✓	✓		✓	
Kim et al. (2010)	C	Min Cost			✓		✓	✓		✓	
Meneghetti and Nardin (2012)	C	Min Cost	✓		✓		✓	✓		✓	
Gu et al. (2013)	C	Max Benefit, Max exchange flows					✓		✓		✓
Hipólito-Valencia et al. (2014)	A,C	Min Cost	✓				✓	✓			✓
Taskhiri et al. (2015)	B	Max Satisfaction			✓	✓	✓	✓		✓	
This research (2016)	C	Min Cost, Max symbiosis	✓	✓		✓	✓	✓		✓	

Chae et al. (2010) proposed a framework to analyze industrial energy consumption in an EIP. The framework was used to construct energy strategies for capturing the wasted heat and wasted water. The presented mathematical model minimized the cost as the objective function to decide energy flows between industries according to the defined energy strategies. They concluded that the establishment of industrial energy complexes provides economic and environmental benefits due to the reduction of energy consumption. The model lacks in analyzing perspectives and applying various objective functions to decide the most efficient energy flows.

Using thermodynamic principles, mass and energy balances, Kim et al. (2010) developed a multi-period mixed integer linear programming model to integrate utility systems in an industrial complex. Companies were divided into “source company” and “sink company” from the viewpoint of a utility network. A source company produces steam, and a sinking company consumes the steam. An objective function was set to minimize the total cost of the raw material cost, investment cost, and operating cost. The approach was applied to companies in the Yeosu Industrial Complex, considering multi-period utility demands. Although the model included the cost of SO_x and greenhouse gasses (GHG) cleanup in the raw material cost, other environmental impacts have not been considered in the model directly. Moreover, the mode is limited to review from the EIP manager point of view.

Meneghetti and Nardin (2012) developed a district-oriented facility management (FM) approach to design a network of firms instead of a single enterprise solution. The presented decision support system helps a FM provider with configuring energy-based kernels of industrial symbiosis. The total annual cost of a system is considered as the objective function to be minimized. The model allows cogenerating power from biomass options as well. The

model does not consider individual perspectives in the network optimization as well as not including environmental impacts in the objective function.

Gu et al. proposed a multi-objective model to maximize the total benefits and entire exchange of flows in an EIP (2013). They applied a tensor matrix to present possible exchanges among industries. A heuristic solution is proposed to solve the multi-objective model. Despite strengths of the model in considering two objectives, it is claimed that the model may fail to provide an optimal solution for all industries included in symbioses (the symbioses could be noneconomic for some businesses). Thus, there is the need for including the perspective analysis from individual's point of view to ensure the validity of a proposed solution. Moreover, the model should consider technical features such as temperature when matching the demand and supply of industries.

Hipólito-Valencia et al. (2014) developed a mathematical programming model for the optimal heat integration of intra and inter-plant heat and Organic Rankine Cycles (ORCs) into an EIP. A set of ORCs was integrated inside the EIP to reuse the waste heat at the low temperature. The recovered heat could be used to generate electricity for selling or utilizing in the system. The model minimizes the total capital cost and operation cost minus the revenue from selling excessive energy. The paper has concluded that additional features such as the complexity of arrangements should be considered during detail design steps to determine a better configuration to fit and to evaluate effects of these factors on the total cost of the EIP.

Taskhiri et al. (2015) developed a fuzzy mathematical model to optimize the wasted heat recovery network in an EIP. Some incinerators were to be located within an EIP to supply

energy for involving industries. The model aimed in maximizing satisfaction for individual industries and the EIP initiator using a fuzzy single objective function. Since incinerators were fed by waste, considerable saving had been observed by replacing the energy demand of industries with the generated energy in incinerators. Despite the economic and environmental benefits, the need to recover the wasted energy within industrial processes is not satisfied.

The main points found in reviewed papers are summarized as follows. Some comprehensive review papers (e.g., Boix et al., 2015) confirm the listed findings.

- Technical features are essential for optimizing the energy symbioses. For example, because the Pinch analysis requires temperature and distance (Hu and Ahmad, 1994), ignoring mentioned technical features in a mathematical model could not provide a feasible solution for industries.
- The existing literature optimizes energy exchange networks using a single objective (mostly the cost minimization). This is against the aim to address economic and environmental concerns in designing industrial symbioses directly.
- In some cases, designing energy symbioses from the EIP perspective could not satisfy individual industries involved in an EIP. Because sharing recovered energy should be economically feasible for suppliers and buyers, individual benefits should be investigated in the proposed approach.

2.8 Methods to evaluate effects of uncertainty in EIPs

Several studies address the optimization of decisions in an EIP (Boix et al., 2015). A review by Kastner et al. (2015) classified the existing models for cultivating symbioses in EIPs. The study shows that modeling methods are typically based on tools developed to

optimize processes including the pinch analysis (Flower and Linnhoff, 1979) and mixed integer linear programming (MILP).

There is a lack of literature for effects of the uncertainty on the optimization of synergy networks. Therefore, a framework to study uncertainty in EIPs is adopted. The uncertainty is widely discussed in areas such as the supply chain optimization (Afshari et al., 2014a; Afshari et al., 2016). The goal of location decisions in the supply chain optimization is to locate the best set of facilities in a network to achieve desired goals. Similarly, in the optimization of flow exchanges in EIPs, the optimum set of symbioses' partners is intended. The framework is adopted using reviewed uncertainties in a supply chain (Simangunsong et al., 2012). Attributes (Skinner et al., 2014) of the framework are presented in Table 2.6.

As presented in Table 2.6, uncertainties are categorized for the business with usual activities in a supply chain as well as equivalent synergies in an EIP. Synergic uncertainties are then assessed using their nature, rank, and type. Despite the existing research in the uncertainty evaluation in supply chains, limited studies have addressed uncertainties in an EIP.

Qiu and Huang (2011) proposed to adopt the supply hub in an industrial park (SHIP) as a public logistics and warehousing services to industries inside an industrial park. They proposed two mathematical models (with and without SHIP) and studied the effect of demand uncertainties in the models. Using a simulation approach, the performance of the models was analyzed. They concluded strategies such as the application of SHIP could be beneficial for an industrial park under the demand uncertainty.

Table 2.6 The framework to study uncertainties in optimization of industrial symbioses

Uncertainty in Supply Chains		Uncertainty in EIPs		Nature	Rank	Type	Existing research
Level	Business as Usual	Level	Industrial symbiosis				
Firms	Product Characteristics	Internal	Input specifications (e.g., price)	A	2	O	
	Process/Manufacturing		Process change; Technology improvement; Operation Failure	E	2	T	
Network	End customer demand		Change of end customer demand	A	1	O	
	Supplier performance		Uncertainty of demand supply	A	1	O	✓
	Configuration, infrastructure & facilities		Uncertainty in matching proper symbioses partners	E	3	S	
	Energy consumption		Uncertainty of energy, water, etc. consumption	A	1	O	✓
External	Economic Environment	External	Price of other energy sources	A	1	S	
	Political Environment		Tax on carbon or other wastes	A	2	S	✓
	Natural Environment		Disasters; weather conditions	A	3	S	

Nature: Aleatoric (A), Epistemic (E);

Rank: Knowing the probabilities (1), Knowing the outcomes (2), Knowing a little (3)

Type: Operational (O), Tactical (T), Strategic (S)

Maes et al. (2011) explored the literature to apply an appropriate energy strategy within the Flanders industrial park. They claimed that the energy management in industrial parks can be integrated into the entire development process and park management. To intensify local synergies, buildings and processes should be clustered for energy exchanges, collective production, and joint contracting of energy services. However, they highlighted that uncertainty and variation of the energy consumption can keep developers from tailoring industrial park design and utilities. The uncertainty of the future tax on carbon or other wastes has been deliberated as well.

Pérez-Valdés et al. (2012) presented a decision making model for a natural-gas powered industrial park. The model maximizes the net present value in the industrial park to determine the type of plants and connections between them. A stochastic mixed-integer

programming model was employed to handle the uncertainty of future prices and costs of raw materials and finished products. It has been discussed that costs of emissions of CO₂ and nitrogen oxides (NO_x) can be considered as a stochastic parameter in the model. The application of the model in a Norwegian industrial park showed the model well suited for analyzing small to moderately sized scenarios considering variations in the most important stochastic parameters.

The existing research for optimization of decisions in EIPs is summarized as follows:

- Although the need for uncertainty analysis is discussed in several studies, the majority of optimization models are formulated for deterministic parameters.
- Compared to the uncertainty studies in the supply chain literature (as shown in Table 2.6), there are several opportunities to optimize decisions of EIPs under uncertainty types.
- Uncertainties in demand and supply, energy prices, and tax on carbon are of major disturbances affecting optimized flow exchanges in the EIPs' topographies. In this regard, addressing these uncertainties in the design of the EIPs would be beneficial for the stakeholders.

Thus, there are opportunities for research in the domain of EIPs to include the uncertainty in the problem formulation as well as in problem solving as highlighted above.

Chapter 3

Modeling and Quantifying Uncertainty in the Product Design Phase

3.1 Introduction

A product life cycle includes stages from the conceptual design to used product at the end of its lifetime. Managing a product life cycle requires solutions for uncertain changes and unpredicted needs for the product. Studies showed that more than a half of initial user requirements will be changed before a project completion (Kobayashi and Maekawa, 2001; Ramzan and Ikram, 2005). Improper management of requirement changes imposes negative consequences to a system or product such as increased complexity (Chen and Zeng, 2006), data loss (Morkos et al., 2010), and wasted time and money (Morkos and Summers, 2010;

Morkos et al., 2012). However, if probable changes and uncertainties are predicted in advance, the chance of design failures (e.g., customer's dissatisfaction) can be reduced. Therefore, it is essential to deal with uncertainties in the product life cycle.

Uncertainty is inevitable in engineering systems. The research showed that "customers' need" is a dominant driver of changes in the product life cycle (Eckert et al., 2009). Uncertainty in the customer need affects the design solution. Customers may update their needs and preferences during the product lifetime. Such uncertainty affects product development (PD) in term of cost, adaptability and time.

It is proved that decisions in the design stage contribute to 70-85% of the total product cost (Besterfield et al., 1995; Ullman, 1997; Cao et al., 2008). In terms of sustainability, these decisions would affect 80-90% of the final performance of a product during its life cycle (May et al., 2011). The design stage decisions contribute to a product quality, durability, and adaptability as well. Therefore, if a designer could identify future changes of a product in the design stage, a proper decision can be made to minimize cost and environmental impacts of the product.

The existing research methods in the product change mainly study the propagation of changes into product components and functions. In other words, the propagation of changes within product structure is discussed regardless of the source of changes (Martin and Ishii; 2002; Yang et al., 2014). The change of customers' preference in a product life cycle is a significant uncertainty for product design. Despite the variety, current qualitative and quantitative methods for the change of preferences (e.g., interview with customers and experts, questionnaires, QFD, marketing research, and engineering methods) have

limitations. For example, the change propagation methods do not provide a metric for comparing design alternatives in different scenarios. Thus, two methods are proposed in this research to bridge the gap of literature. Both methods use innovative mechanisms to capture and transfer changes into the product design.

The goal of this research is to quantify changes of customers' preferences during the lifetime of a product. By quantifying the changes, a designer will be able to provide appropriate solutions in the product design stage. The research is to find ways to measure future changes of customers' needs in the design stage. If the quantified changes of customers' preferences are provided to designers, product components to meet functional requirements and design parameters related to the changes can be considered to meet the changing need.

The proposed agent-based model (ABM) simulates changing events and interactions in a product life cycle. The Big Data method is proposed for further improvements of the presented ABM in term of social and technical factors, and the study scope. Using Big Data analytics, product and user data can be collected to be used for product improvement. Among discussed types of Big Data analytics including descriptive, predictive, and prescriptive data analysis, this research develops a prescriptive analytics for product design process. In this type of Big Data analytics, not only past trends are used to mine user data (descriptive analysis), the future trends are also predicted (predictive analysis). Solutions for product design based on effects analysis are then proposed. The efficiency of methods is justified based on the convergence of predicted changes to the real changes of a product.

3.2 Proposed methods to model and quantify uncertainty under user preference changes

Existing research recommended two main approaches for changes in the product development processes: approaches focusing on the early design process (to anticipate the need for changes), and methods to predict the impact of changes (e.g., Eckert et al., 2009). In this regard, two methods are proposed to predict changes and to transfer the changes into the product development process. Both methods use modules for the change prediction and change transferring.

3.2.1 Agent-based modeling for the prediction and transferring changes into the product development

A model is extended based on the diffusion theory (Bass, 1969) for the prediction of changes of customers' preferences (Afshari et al., 2013). The model addresses needs for the quantification and transferring changes into the product development as shown in Figure 3.1. The model has multi-domain (social and technical elements embedded), scenario-enabled, and customer-oriented features.

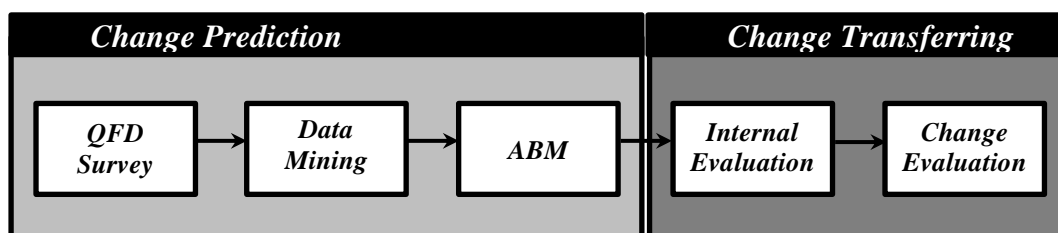


Figure 3.1 Schematic of the proposed agent-based model (ABM)

The model consists of five processes including QFD survey, data mining, ABM, internal evaluation and change evaluation as shown in Figure 3.1. A product is first decomposed into its components. The list of product components is used to define a QFD survey. In addition,

other decisions such as the scope of study, market, and details of the product specifications are necessary to initiate the model. Using an initial House of Quality (HoQ) in the QFD technique, collected customers' preferences are transferred into engineering specifications (functional requirements). The functional requirements (FRs) are then mapped into product functional parts. These mapping matrices (customers' preferences into FRs, and FRs into parts) are essential to measure parameters in next steps as presented in Appendix A.

Data mining is an important step in the proposed model. Some tools and analyses such as statistical analysis, prediction methods, quantitative and qualitative data collection methods are used to estimate the value of parameters. Trends in the technology evolution are estimated for the list of components and subsystems. Using retrospective data or consulting with experts and manufacturers are two common methods for the quantitative trend estimation.

The collected data are applied to simulate a product life cycle using agent-based modeling. Ability of agent-based models to simulate multiple interactions of agents in complex systems is used to model and quantify effects of external changes on customers' preferences. A process of agent-based modeling is presented in Figure 3.2.

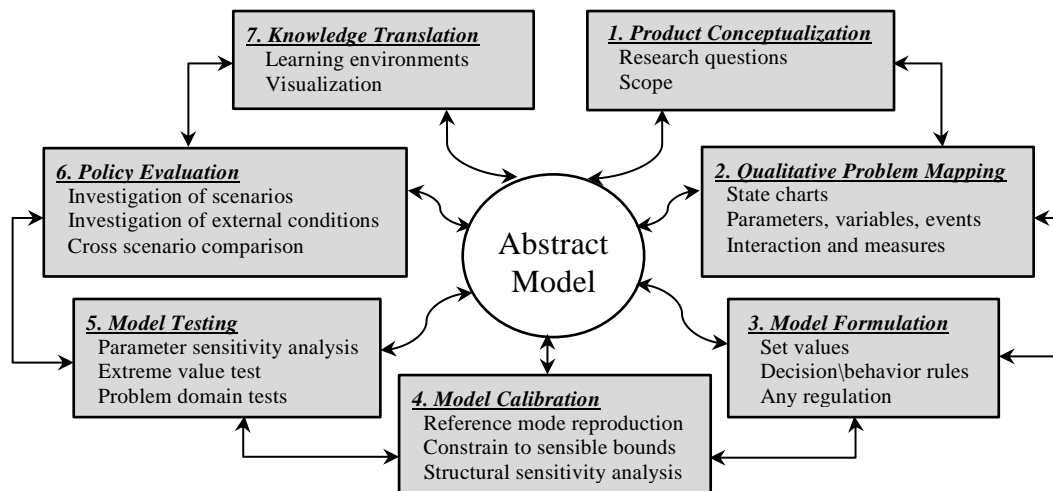


Figure 3.2 Process of agent-based modeling

For ABM, research questions, scope, and objectives of the simulation should be defined. The collected data are used to define required parameters, variables, and interactions in the model. Events and specific regulations are then modeled. The rest of steps for the agent-based modeling are discussed using a product.

Figure 3.3 presents a schematic view of interactions in the proposed model. The model quantifies the interaction of customer to customer, and customer to technology as shown with 1 and 2 in Figure 3.3.

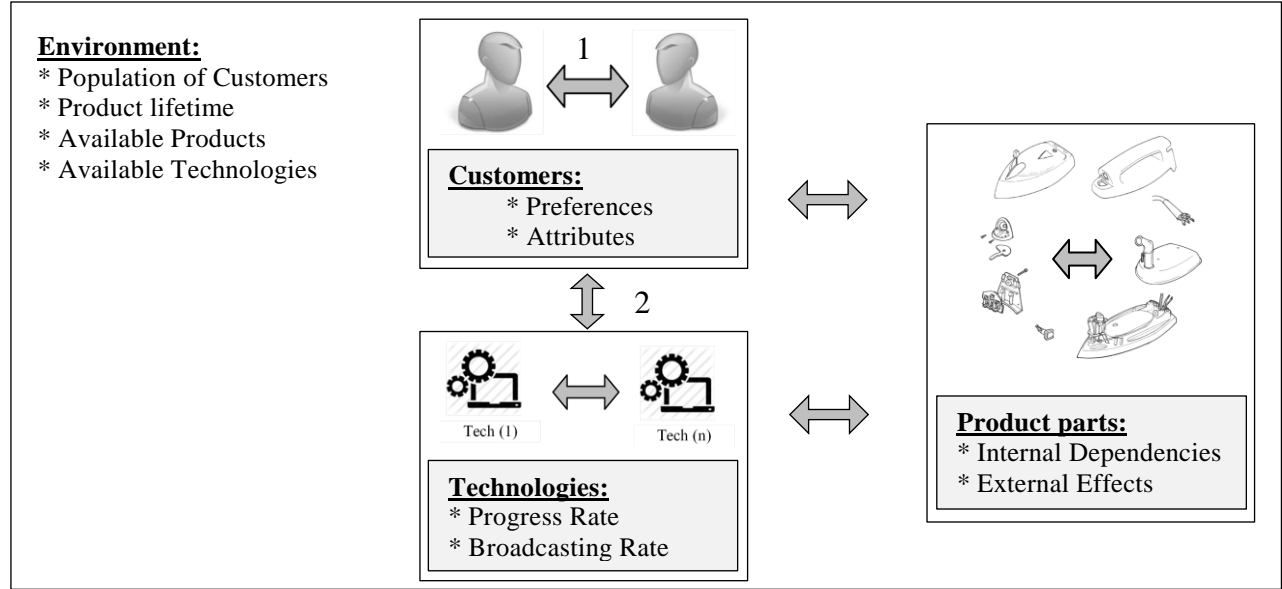


Figure 3.3 Schematic view of elements and interactions in the proposed agent-based model

It is proved that exploring user's perception and the adoption for a specific product is useful for understanding the design of product features (Tsai and Ho, 2013). The basis of the agent-based model is an extended version of basic diffusion theory shown in Equation 3.1. The aim is to evaluate the effects of social interactions and mass media on people's preferences when such changes of preferences matters for a manufacturer.

$$\frac{dY(t)}{dt} = m \cdot [\bar{Y} - Y(t)] + n \cdot \frac{Y(t)}{\bar{Y}} \cdot [\bar{Y} - Y(t)] \quad (3.1)$$

In Equation (3.1), $Y(t)$ is the total number of customers who adopt new products at time t . \bar{Y} is the total number of potential adopters. The coefficient m is the share of innovation (hence, first part of the equation shows the leading customers who buy a new product without the influence of others). The coefficient n represents the share of imitation (second part of Equation (3.1) shows the people who buy a new product influenced by others). To propose a mathematical formulation for changes in customers' preferences, events affecting the

preferences are identified. Technology improvements and people interactions are considered as two major events invoking uncertainty into the model. It is considered that people interaction happens more often than the technology improvement (assuming people interaction and technology evolution events to occur in period t and P respectively, $t < P$).

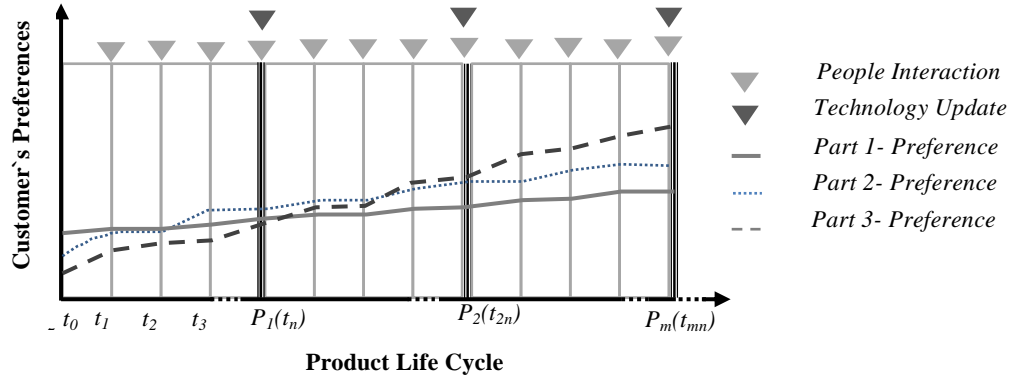


Figure 3.4 Summary of events affecting customer's preferences in a product life cycle

At $t=P_1$, two different events affect the preferences. The first event is the accumulation of interactions between customers, and the second event is the broadcasting and adoption of a new technology by leading customers. Equations (3.2) and (3.3) formulate the events.

$$CP_{i,j}(t_n) = \sum_{t=1}^{t_n} \gamma_{frd}(i,j,t) \cdot [(1 - \omega_{frd})CP_{i,j}(t-1) + \omega_{frd} \cdot P_{frd}] + (1 - \gamma_{frd}(i,j,t)) \cdot CP_{i,j}(t-1) \quad (3.2)$$

$$CP_{i,j}(Pr_1) = \varphi_{tech}(i,j,P_1) \cdot [(1 - \omega_{tech})CP_{i,j}(t_n) + \omega_{tech} \cdot P_{tech}] + (1 - \varphi_{tech}(i,j,P_1)) \cdot CP_{i,j}(t_n) \quad (3.3)$$

A customer (i) is autonomous to adopt a new technology for component (j) in interactions with their friends; the probability of adoption from friends ($\gamma_{frd}(i,j,t)$) is

defined using Bernoulli distribution with $p=0.5$. At the end of a product life cycle, mutual effects of both events are measured using Equation (3.4).

$$CP_{i,j} = \sum_{t=t_1}^T \varphi_{tech}(i,j,P_m) \cdot [(1 - \omega_{tech})CP_{i,j}(P_m) + \omega_{tech} \cdot R_{tech}(j)] + (1 - \varphi_{tech}(i,j,P_m)) \cdot CP_{i,j}(P_m) \quad (3.4)$$

In Equation (3.4), I refers to the set of customers ($i \in I$), J stands for the set of product parts and components ($j \in J$), and T defines the time of events ($t \in P$), and ($P \in T$). The rest of parameters and variables are as follows:

$CP_{i,j}(t)$	Preference of customer i for part j at time t ,
$\gamma_{frd}(i,j,t)$	Adoption probability of customer i for part j at time t when interacting with a leading friend,
ω_{frd}	Weight of imitation (inspired by friends) in adopting a new technology,
P_{frd}	Technology preference of a friend,
$\varphi_{tech}(i,j,P)$	Adoption probability of customer i for part j at time P a new technology is introduced,
ω_{tech}	Weight of innovation (inspired by media) in adopting a new technology,
$R_{tech}(j)$	Rate of technology improvement for part j ,
\overline{CP}_j	Average customers' preference for part j

The customer's preferences are used to measure average part's preferences at the end of the product life cycle using Equation (3.5).

$$\overline{CP}_j = \sum_{i=1}^I CP_{i,j}/I \quad \text{for } j \in J \quad (3.5)$$

For a large population of customers, it is difficult to run the explained measurements in Equations (3.2) to (3.5). Hence, interactions are modeled using software packages. Table 3.1 summarizes the required attributes in the proposed agent-based model. The elements introduced in Table 3.1 are used to simulate interactions and influences of agents and environments during a product lifetime.

Table 3.1 Summary of elements in the proposed agent-based model

Standard ABM elements	In proposed agent-based method	Equivalent in formulations	Type
Agent	Customer's preference for each part	$CP_{i,j}(t)$	Agent
Agent attributes	Activity; flexibility; sociability	N/A; $\varphi_{tech}(i, j, P)$; $\gamma_{frd}(i, j, t)$	Parameter
Agent to agent interaction	Customers' interaction	Equation (3.2)	Event
Environment attributes	Technology progress rate; technology broadcasting time	$R_{tech}(j)$; P_i	Parameter
Agent to environment interaction	Technology adoption	Equation (3.3)	Event
Other attributes	Product lifetime; number of customers; number of technologies; product components	$P_m(t_{mn})$; I ; N/A; J	Parameter

The output of agent-based modeling is the quantified value of changes in customers' preferences affected by interactions. The changes in customers' preferences are transferred into product components. The magnitude of changes for each product component and subsystem are measured. This is considered as the end of the change prediction for studying external elements of the product structure.

Transferring external changes into product components is the next step to evaluate interdependencies between components. Two items are considered: the magnitude of changes as the output of the agent-based model, and the dependencies between parts to evaluate the internal effects. Hence, a new matrix is defined to elicit the dependencies between parts. Assuming INT as the dependency matrix of n part, and vector MAG as the magnitude of changes transferred to product parts from external interactions during a product life cycle, vector CHG is evaluated as the total changes transferred into all components of a product as shown in Equations (3.6) and (3.7).

$$CHG = INT \times MAG \quad (3.6)$$

$$\begin{bmatrix} CHG_1 \\ \vdots \\ CHG_n \end{bmatrix} = \begin{bmatrix} INT_{1,1} & \cdots & INT_{1,n} \\ \vdots & \ddots & \vdots \\ INT_{n,1} & \cdots & INT_{n,n} \end{bmatrix} \times \begin{bmatrix} MAG_1 \\ \vdots \\ MAG_n \end{bmatrix} \quad (3.7)$$

The dependency matrix (INT) is evaluated using a cross functional group of experts and product designers. Obviously, the diagonal elements on INT are valued as zero. Finally, vector CHG is used for the product revision and redesign decisions.

3.2.2 Big Data analytics approach for the prediction and transferring changes into product development

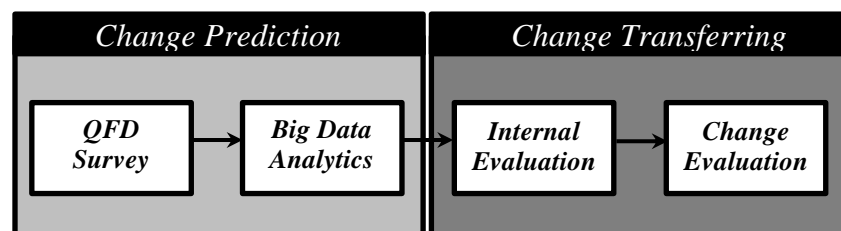
Analyzing uncertain and probabilistic data using Big Data analytics is mostly based on traditional databases and data sets that provide some errors in the model (Pei, 2013). Hence, a new method to quantify changes in a product life cycle is proposed using Big Data analytics. The method is based on huge data sets publicly available to investigate changes in product development process (Afshari and Peng, 2015a). This is the first time that internal changes of parts are measured under external effects using Big Data analytics.

The proposed ABM considers updates in product-related technologies as technical events while there are many other technical events that may also affect technical knowledge of customers as well. The ABM simulates agents' interactions in a limited scope of time and location. Such isolation is barely witnessed in the real product life cycle. Thus, the Big Data analytics method is proposed to overcome the limitations by using the real data. Because the data used for the analyses entails the consequences of several social, technical, and environmental factors, the analysis quality is ensured and further simulation is not required. Table 3.2 summarizes the improvements achieved using the Big Data analytics method.

Table 3.2 Comparison of the proposed methods in terms of technical factors, social factors, and scope of data

Criteria		Agent-based modeling	Big Data analytics
Technical	Product technology evolution	✓	✓
	Global technology evolution		✓
Social	Friends and Media	✓	✓
	Regulations, politics, etc.		✓
Scope of data	All times and locations		✓
	Customized scope	Limited to simulation	✓

This study uses three years analyzed data to conclude the interconnectedness between customers' preferences. The proposed model applies potentials of the social network analysis to evaluate changes in product design as presented in Figure 3.5. The method initiates with choosing a product and defining scope and market. By decomposing the product into its components, one can collect customers' data called the voice of customer. Using the QFD technique, the data are transferred into functional requirements (FRs). Some essential decisions such as customer region, sample size of survey, and members of the expert team are made in this step. The output of QFD survey is a list of functional requirements that is used for the keyword search and data aggregation in the next step.

**Figure 3.5** Proposed method to quantify changes of product using Big Data Analytics (BDA)

Lack of access to required data is a common challenge affecting most of the Big Data analyses. The complexity of available tools and scarcity of reliable data limit Big Data analyses. Google Trends and Google Correlate are two online tools for researchers based on Google search. Google Trends indicates how often a particular search-term or keyword is searched either in total or in detail (languages and regions in the world) since 2004. Google Correlate searches across millions of candidate query time series to find the best matches for selected time series. Google Correlate finds web searched terms according to user-provided time series of data. Google Correlate algorithm uses efficient techniques such as Asymmetric Hashing that enables fast searches, high-recall results and supported holdouts (Vanderkam et al., 2013). Hence, Google Correlate provides optimal predictions for researchers efficiently. Both tools have been popular search tools in different fields. For example, in healthcare research, Google Trends was used to track Influenza-like-illnesses in a population (Ginsberg et al., 2009). Also in business, Preis et al. (2010) presented a correlation between Google Trends data searched for a company and transactions volume of its stocks in market per week. The efficiency of proposed examples in addition to the simplicity and applicability of Google tools inspired us to use them as a valuable source for Big Data analytics as shown in Figure 3.6.

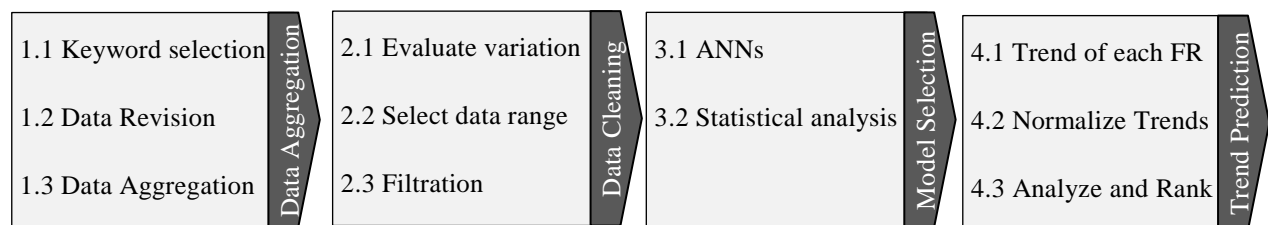


Figure 3.6 Detail transactions in Big Data Analytics

An effective data collection using Google Trends requires accurate keywords. To generate proper keywords for search, a list of FRs prepared by the QFD survey is utilized. There are multiple cases that keywords should be revised to start over the search. It should be checked if the collected data are properly distributed on the world map (or defined scope of study).

In Data Cleaning, also called data cleansing or scrubbing, inconsistencies and errors within the data are removed to improve the quality of data prepared for trend predictions. There are several methods and tools to clean the data. For a product life cycle, a major concern in data cleaning is unusual fluctuations in the searched trends. To remove such sudden changes, the reasons should be investigated and unacceptable results should be removed. In our case, the search trends about product features abruptly change when a new product is about to release. Moreover, the collected data for all keywords should be for similar time.

To estimate the trends in data sets, several tools and methods are available (Petropoulos et al., 2013). Artificial Neural Networks (ANNs) and Statistical analysis methods are widely used in the literature for predicting the trends.

Finally, the trends for FRs are estimated and normalized. Normalization helps comparing the trends in a unique framework. The normalized trends are evaluated to highlight the most affected functional requirements. The output of Big Data analytics is a vector of quantified values of changes transferred into components of a product.

Both the ABM method and Big Data analytic method use the “change transferring” module as shown in Figure 3.5. The advantage is providing a common basis to compare results. In the next section, a product is used to apply the proposed method.

3.3 Application of proposed methods

Proposed methods are used to quantify changes of a smartphone. A smartphone consists of multiple components with interdependencies of some parts, which makes it a good example for applying both methods (see Figure 3.7). The mutual steps in the proposed model are described together including: QFD survey, internal evaluation (see Table 3.4), and change evaluation (see Table 3.6). Moreover, the proposed methods are compared with the method based on Design for Variety (Nadadur et al., 2012). To keep a consistency between measurements, similar data and QFD matrices are used in the proposed methods as presented in Appendix A.



Figure 3.7 Exploded view of the smartphone to model changes in its life cycle (Afshari and Peng, 2015b)

The QFD technique uses two transforming matrices as depicted in Figure 3.8. Using a survey, customer’s preferences, features, and expectations from a smartphone were collected. An expert team was employed to transfer customers’ preferences into functional

requirements (FRs) as presented in Appendix A, Figure A.1. The FRs were then mapped into individual components.

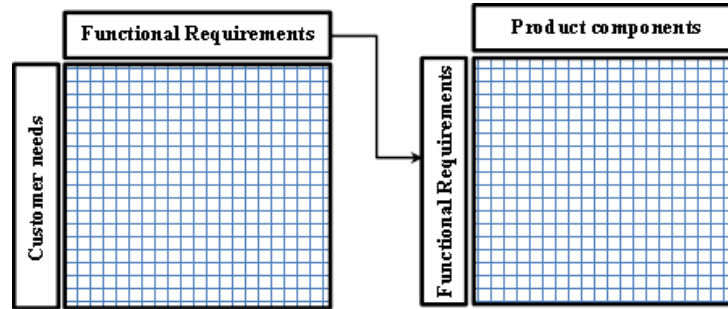


Figure 3.8 Houses of quality in the QFD technique

3.3.1 Application of the agent-based model for the smartphone

The current and future technologies for each part are searched using a list of components. One approach is to consult with manufacturers and follow their strategic plans to ensure the accuracy of estimations. To obtain the value of parameters related to events and interactions in Table 3.1, associate rule mining and classification algorithms are used (Lee et al., 2015). These algorithms are known as efficient techniques to extract unknown parameters in databases. After preparing the list of values for defined parameters as presented in Table 3.3, the software package is used to simulate the product life cycle.

Table 3.3 The values utilized for the defined parameters in the studied smartphone

Parameter	Value	Parameter	Value
$CP_{ij}(t)$	Initial value = 0	$\varphi_{tech}(i, j, P)$	0.25
$\gamma_{frd}(i, j, t)$	0.5	ω_{tech}	0.1
ω_{frd}	0.1	$R_{tech}(j)$	Adopted from (Nadadur et al., 2012)
P_{frd}	Initial value = 0		

AnyLogic 6.8 is used to simulate the proposed model. The following discussion is based on the AnyLogic, but the presented logic is applicable for other software packages. Initial setup is defining agents and the type of network. Customers are defined as agents and a list of preferences is assigned to each agent. Agents' interactions with other agents and with the environments are modeled using state charts as presented in Figure 3.9.

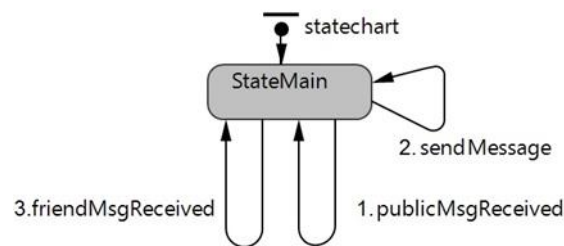


Figure 3.9 Defined state chart for agents' interactions

Customers are divided into two groups. Technology followers update their preferences when interacting with public media (e.g., advertisement, technical reports, and social networks). This event is shown as “publicMsgReceived” in Figure 3.9. After updating preferences based on the advertised technology, the second interaction commences called “sendMessage”. In this interaction, agents broadcast their preference to other connected friends. As agents are autonomous, they may accept other agents' invitation to update the preferences. This is organized by defining a flexibility rate for each agent. If the flexibility rate of a receiving agent is more than a sender agent, preferences of the receiving agent are updated, shown as “friendMsgReceived”. Otherwise, agents will not update their preferences.

In the Anylogic package, the type of a network defines how the agents are connected together. If “Ring Lattice” is selected, agents will interact to local agents. “Random Network” denotes global connections. “Small World” is the combination of both described

networks. The type of a network is selected as “Small World” to resemble real world conditions

AnyLogic provides a step-wised graphical representation for simulation, illustrated in Figure 3.10. In the figure, friends are connected together using lines. After initializing the simulation, all agents are set in blue color. Following interactions in Figure 3.9, the public message by media is sent to all agents. Technology follower agents who updated their preferences will show up in green color. Specific periods are set for broadcasting technologies and interactions with friends. If an agent accepts a friend’s invitation, its preferences are updated and its color changes to red. The simulation continues up to a particular time (three years) to resemble the product life cycle.

At the end, an average of preferences is measured as presented in Equations (3.4) and (3.5). The output is quantified values of changes transferred into individual components of the smartphone. To finalize the quantified values of changes, the effects of internal changes should be evaluated. The expert team is again employed to evaluate the relationship between parts as formulated in matrix INT of Equation (3.7). Table 3.4 summarizes the analysis of dependencies between components of the smartphone. Dependency values are not symmetric to diagonal; therefore, it matters if a component is sending or receiving a change.

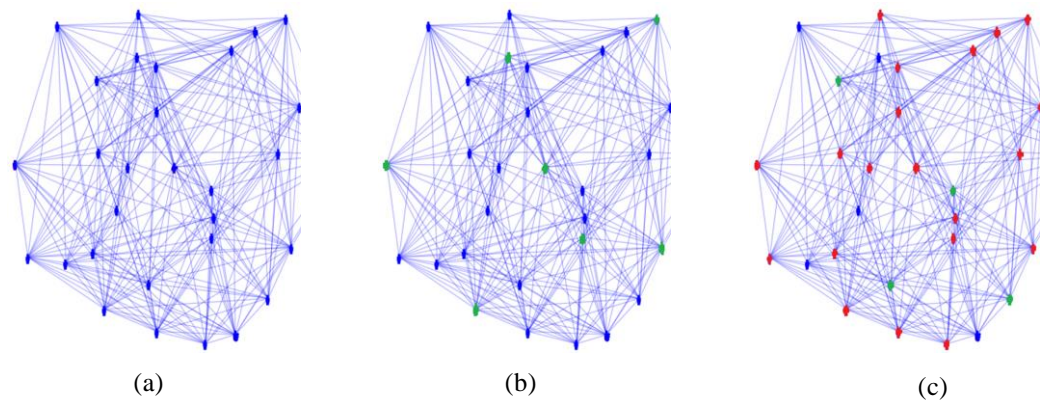


Figure 3.10 Graphical representation of simulation steps: (a) Start-up of simulation, all agents are in blue color, (b) Technology broadcasting, technology follower agents turn to green, (c) agents accepting a friend's invitation turn to red

Table 3.4 Evaluation of interdependencies between components of the studied smartphone

To		A	B	C	D	E	F	G	H	I	J	K	L	M	N	Sender
From																
Display	A	0	6	0	3	0	0	0	0	1	3	0	0	6	0	19
Touchscreen	B	6	0	0	1	0	0	0	0	1	1	0	0	3	0	12
Sound	C	0	0	0	1	0	0	0	0	1	1	0	0	0	1	4
Processor	D	3	3	1	0	1	1	6	3	6	3	1	6	0	0	34
DRAM memory	E	1	1	1	0	0	3	0	0	1	0	0	1	0	0	8
Flash Memory	F	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
Data transfer	G	0	0	0	3	0	0	0	9	3	1	1	0	0	3	20
Internet-connectivity	H	0	0	0	1	1	0	6	0	1	3	1	0	0	0	13
Software	I	1	0	1	3	0	0	0	0	0	1	0	0	0	1	7
Battery	J	1	1	1	1	0	0	0	0	1	0	0	1	1	3	10
GPS	K	0	0	0	1	0	0	0	0	1	0	0	0	0	0	2
Cameras	L	0	0	0	1	0	0	0	0	1	3	0	0	1	0	6
Outer facing	M	6	1	0	0	0	0	0	0	0	0	0	0	0	0	7
Physical Interfaces	N	0	0	0	0	0	0	0	0	1	6	0	0	1	0	8
Receiver		18	12	4	15	3	4	12	12	18	22	3	8	12	8	

Dependencies are rated between 9 (if small changes in the specifications impact the receiving component) to 0 (No specifications affecting component). Summation of assigned rates shows that changes in some components have significant impacts on others (e.g., processor), and some components are vulnerable to changes of other components (e.g.,

battery). Using Equation (3.7), the mutual effects of external and internal changes are evaluated for each component. Result is discussed in the Analysis and Discussion section.

3.3.2 Application of Big Data Analytics (BDA) for the smartphone

Figure 3.11 shows that despite decreasing trends for searching “cell phone” and “mobile phone” terms, the interest for “smartphone” is increasing, particularly since 2010. This is a simple example to demonstrate how Google Trends works for our research. Because it is proven that there is a correlation between google search and success of a product in the market, the changes in customers’ preferences, functional requirements (FRs), and product components are targeted to evaluate using the proposed method. Moreover, to increase the clarity of the proposed methods, a sequence of analysis, outputs, and referred figures and tables is presented in Figure 3.12.

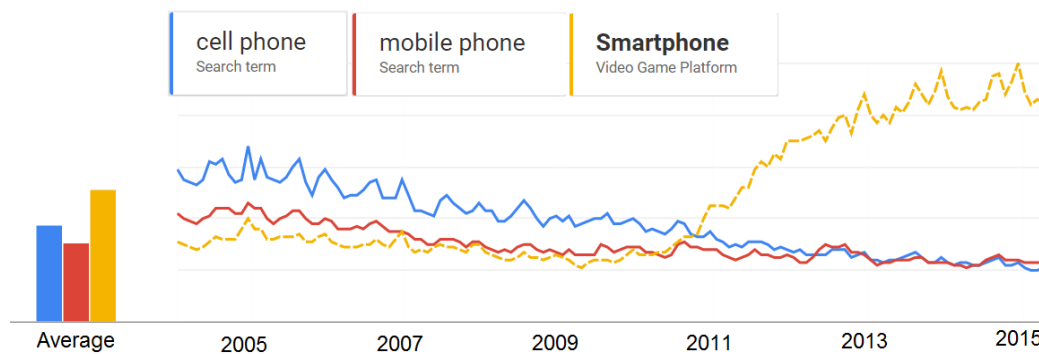


Figure 3.11 Interest over time for selected key words search "Cell Phone", Mobile Phone", and "Smartphone" using Google Trends

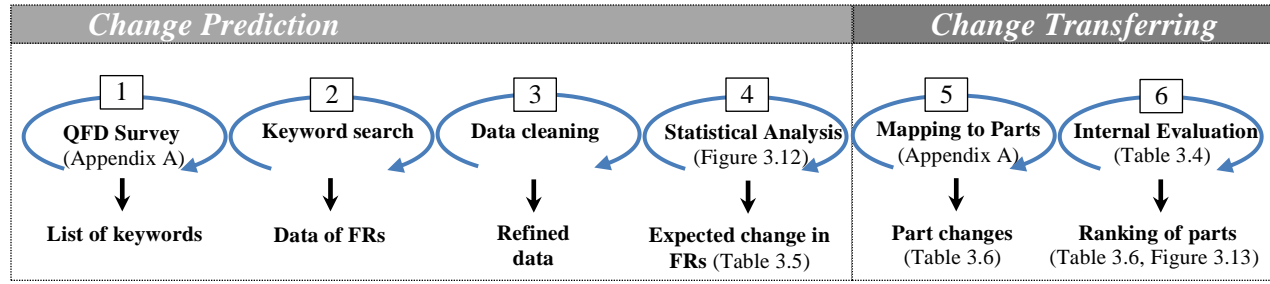


Figure 3.12 Sequence of analysis for the proposed Big Data analytics methods

To keep the consistency of results and being able to compare proposed methods, the same results from the QFD survey are used in the proposed agent-based method. The output of the first QFD matrix is a list of FRs, which is used to choose keywords. These keywords were then used to extract data sets via Google Trends.

The source of Big Data used in this research is the huge Google searches conducted across the world. In terms of the volume and size of data, it is a big challenge to use such huge searched items; however, the Google has provided efficient tools including “Google Trends” and “Google Correlate” to extract required data from searched items. In other words, the tools can summarize and categorize Big Data to be used for further analysis. Thus, using keywords through Google Trends we can access huge data in a classified order.

Following transactions proposed in Figure 3.6, it was noticed that in several cases the selected keywords could not represent the corresponding data set (e.g., limited to specific locations or countries, abrupt jumps, unknown distributions). Hence, the keywords were revised to collect proper data sets. If several data sets were collected for a unique keyword, data sets should be aggregated. Google Trends concludes each keyword search with a simple downloadable format; therefore, the data sets for each FR did not require aggregation. For the

smartphone, all keywords across the world in English language are searched since 2004. The collected data are refined using a data analytics method described in following paragraphs.

Data cleaning is essential for using Google Trends. Thus, variations within each data set (stemming from seasonal effects or any unpredictable events) are monitored. If a point of data is recognised as a noise, the point is deleted to maintain validity of trend. It is noticed that the trend for some FRs has been shifted or changed several times since 2004. Because of such a long period, multiple events could contribute to the changes. For example, some events in macro economy (e.g., recession) had affected customers' behavior in specific years. Filtering the data to specific periods could remove the reviewed effects.

After data cleaning, a statistical analysis method is used to measure the trend for each FR. Different regression types were tested to identify the best fit with the least error. Linear regression is the best correlation coefficient among regression types to measure the trends of FRs. In Figure 3.13, two examples of the regression analysis for FRs are presented. The slope of a trend line represents the amount of changes in interests over time for each FR.

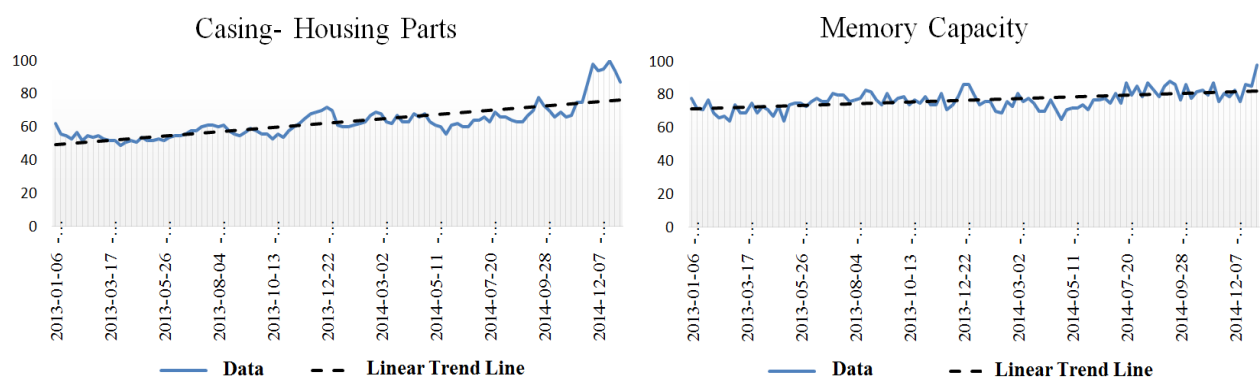


Figure 3.13 Measured trends for FRs using a linear regression model

Considering the linear regression equation ($y = ax + b$), the values of slope (a) and intercept (b) are listed in Table 3.5. Also, the measured values of slopes are normalized to compare changes of interests over time for twenty-five FRs. After mapping FRs into related components of the smartphone (Figure A.2 in Appendix A), one could measure the external changes (caused by changes in customers' preferences) transferred into the components.

Table 3.5 Measurement of changes transferred into each FR using linear regression equations

#	FRs	a	b	Norm a	#	FRs	a	b	Norm a
1	Display size	0.102	40.49	4.18	14	Baseband processor	0.077	19.55	3.18
2	Display Resolution	0.038	62.17	1.57	15	Baseband support	0.094	41.54	3.87
3	Touch-size	0.075	70.76	3.10	16	Download speed	0.085	57.00	3.51
4	Touch-tech	0.152	64.45	6.26	17	WiFi speed Standards	0.208	42.38	8.56
5	Audio codec	0.027	49.94	1.10	18	Bluetooth	0.083	35.56	3.40
6	Mic sensitivity	0.070	60.08	2.89	19	Capacity - power	0.180	55.49	7.43
7	Speaker loudness	0.056	25.35	2.32	20	Connector cable	0.204	51.82	8.39
8	Processing speed	0.155	51.81	6.37	21	GPS	0.067	43.27	2.77
9	Memory capacity	0.105	71.19	4.32	22	Cameras-resolution	0.016	14.73	0.68
10	Operating System	0.107	42.96	4.41	23	Cameras-video	0.059	21.69	2.42
11	Apps	0.107	67.99	4.42	24	Casing-housing parts	0.258	49.38	10.63
12	GSM &CDMA	0.034	29.35	1.42	25	Casing-Interactive parts	0.034	15.04	1.39
13	Frequencies	0.034	29.35	1.42					

To evaluate the internal dependencies between each two components of the smartphone, the same matrix *INT* in the agent-based method is utilized. Detail results for transferring changes into components considering interdependencies are presented in the next section.

3.4 Analysis and discussion

In both proposed methods, the second module (transferring changes) is common. Using Equation (3.7) and interdependency analysis in Table 3.4, the total changes transferred into components of the smartphone are measured. Quantified values of changes are presented in Table 3.6. To compare efficiency of the proposed methods, the changes (CHG_{real}) in the components of the smartphone are presented since the phone was introduced to the market.

The magnitudes of changes are normalized to compare the efficiency of proposed methods. Error measurement indexes are used to compare normalized magnitudes of the changes with the real changes. The best method should present the least measurement error to real changes of the smartphone. Summary of error measurements for the methods is shown in Table 3.7. In parallel, the proposed methods in this research are compared with the Design for Variety method applied by Nadadur et al. (2012); therefore, GVI index is measured for the smartphone.

Table 3.6 Evaluated magnitude of changes (*MAG*) for each component using proposed methods and real changes of the smartphone

	MAG_{ABM}	MAG_{BDA}	CHG_{ABM}		CHG_{BDA}		CHG_{real}	
			Value	Norm	Value	Norm	Value	Norm
Display	11.93	12.65	913.1	24.08	1346.8	36.26	2	33.33
Touchscreen	21.93	49.55	684.8	18.06	1059.4	28.52	4	66.67
Sound	7.41	7.70	204.8	5.40	194.5	5.24	4	66.67
Processor	100.00	97.02	3791.6	100.0	3714.1	100.0	6	100.0
DRAM memory	19.21	15.20	293.6	7.74	254.3	6.85	3	50.00
Flash Memory	18.26	13.15	175.9	4.64	155.8	4.19	3	50.00
Data transfer	41.33	40.95	1556.7	41.06	1536.1	41.36	5	83.33
Internet-connectivity	21.67	22.49	953.7	25.15	952.0	25.63	3	50.00
Software	55.03	44.10	1225.6	32.32	1199.9	32.31	6	100.0
Battery	0.99	7.43	679.3	17.92	884.9	23.83	6	100.0
GPS	4.14	16.64	171.3	4.52	193.7	5.22	2	33.33
Cameras	10.55	18.49	683.5	18.03	715.7	19.27	4	66.67
Outer facing	29.93	75.23	376.9	9.94	813.1	21.89	4	66.67
Physical Interfaces	18.54	36.06	337.7	8.91	485.4	13.07	2	33.33

Table 3.7 Error measurement for the proposed methods

Source Data	Error index	MAG_{ABM}	MAG_{BDA}	CHG_{ABM}	CHG_{BDA}	GVI
Real magnitude of Changes	Least Absolute Deviation	186.5	226.0	194.7	169.0	295.0
	Least Deviation	-152.5	-9.3	-162.2	-116.4	137.0
	Mean Percentage Error	-31.33	19.06	-34.22	-21.28	58.04
	Mean Squared Error	6.71	4.76	2.59	1.78	5.03
Rank in real number of changes	Least Absolute Deviation	44.0	48.0	41.0	43.0	46.0
	Least Deviation	0.0	0.0	0.0	0.0	-25.0
	Mean Percentage Error	33.98	40.19	19.73	20.22	6.18
	Mean Squared Error	3.21	3.22	1.64	1.40	2.16

It is noticed in Table 3.7 that the proposed methods have shown the least error. Comparing error indexes for the real magnitude of changes determines that the second proposed method (BDA) has the most convergence to the real changes of the smartphone. It can be concluded that evaluating the changes using Big Data analytics is the best method when both external and internal effects are measured. Ranks in real number of changes propose that the agent-based method provides the minimum error. This is the proof of the efficiency for proposed methods.

Evaluating the internal dependencies between parts (*INT*) in both methods has provided a higher convergence to the real changes of the smartphone. In Equation (3.7), the vector of *MAG* is multiplied to the matrix of *INT* to ensure that dependencies between parts are considered in modeling and quantification of changes. Results in Table 3.7 show that such consideration for change transferring is effective. Reviewing the error indexes per MAG_{ABM} and MAG_{BDA} columns, the error indexes are reduced when compared to CHG_{ABM} and CHG_{BDA} . Although the efficiency of the proposed method is presented, it is believed that the current method to apply internal dependencies can be further improved in future work.

For the proposed agent-based method, a sensitivity analysis was conducted. The main purpose is to assess effects of different values of parameters in the agent-based simulation. If the method can provide stable results under different scenarios, it is concluded that the results of the method is reliable in the selected environment. Otherwise, sensitive parameters are highlighted for the designers to monitor. Some scenarios are defined and the rank of changes is measured as shown in Table 3.8. The ranks are stable in 5 out of 8 scenarios. Some minor changes are witnessed for the scenarios 6-8. Therefore, the reduction of product life cycle,

the rate of imitation from others, and rate of innovation are assessed as important parameters. Obviously, the sensitivity analysis is not necessary for the Big Data analytics as the parameters are obtained from real data sets.

Table 3.8 Sensitivity analysis for the selected parameters in the proposed agent-based method

Scenarios	Direction	Ranking of the changes in the smartphone parts													
		A	B	C	D	E	F	G	H	I	J	K	L	M	N
Number of customers	↑	11	8	12	1	5	6	3	7	2	14	13	10	4	9
Number of friends	↑	11	8	12	1	5	6	3	7	2	14	13	10	4	9
Number of far friends	↑	11	8	12	1	5	6	3	7	2	14	13	10	4	9
Rate of Tech. evolution	↑	11	8	12	1	5	6	3	7	2	14	13	10	4	9
Product life cycle	↑	11	8	12	1	5	6	3	7	2	14	13	10	4	9
Product life cycle	↓	10	5	12	1	7	9	3	6	2	14	13	11	4	8
Rate of imitation	↑↓	10	5	12	1	7	9	3	6	2	14	13	11	4	8
Rate of innovation	↑↓	10	5	12	1	7	9	3	6	2	14	13	11	4	8

Finally, the quantified changes of parts in the smartphone life cycle are ranked. The proposed methods have shown a good prediction of changes in the product life cycle, as the graphical presentation illustrates in Figure 3.14.

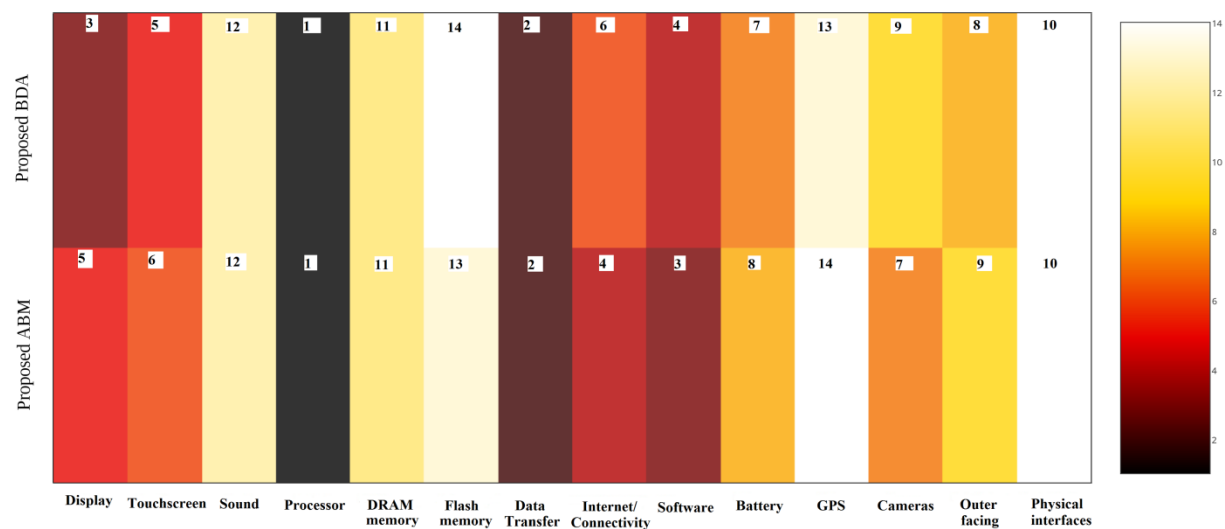


Figure 3.14 Ranking of the components using the proposed agent-based method and Big Data analytics method

Both methods reported very similar rankings of the parts. Top five parts are processor, data transfer, display, software and touchscreen. Therefore, designers can make proper strategies to deal with changes in the smartphone components in the design stage. Martin and Ishii (2002) presented a list of strategies to manage changes in the product life cycle. It is believed that an accurate knowledge on quantified changes of product components in the design stage can help designers in revising product to maximize customers' satisfaction. Consequently, such approaches improve manufacturers' profitability and market share by continuously satisfying its customers.

The research conducted in this Chapter has been published in the following journal and conference proceedings:

- Afshari H, Peng Q. Modeling and quantifying uncertainty in the product design phase for effects of user preference changes. *Industrial Management & Data Systems*. 2015b; 115(9):1637-65.
- Afshari H, Peng Q, Gu P. An agent-based method to investigate customers' preference in product lifecycle. In *ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*. 2013; V004T05A046-V004T05A046.
- Afshari H, Peng Q. Modeling Evolution of Uncertainty in Sustainable Product Design. In *ASME 2014 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference* 2014; V004T06A052-V004T06A052.

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- Afshari H, Peng Q. Using Big Data to minimize uncertainty effects in adaptable product design. In ASME 2015 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. 2015a; V004T05A052-V004T05A052.

Chapter 4

Design Optimization for Sustainable Products under Uncertainty

4.1 Introduction

Products and services are expected to meet varying customers' preferences with the diversity and short life cycle of products in the competitive market (Beuren et al., 2013). Diversified products require higher costs and more development efforts for industries than the traditional product using mass manufacturing (Kohtamäki et al., 2013; Reim et al., 2015). Moreover, a designer should consider multiple objectives for a product such as reasonable cost, high quality, and environmentally friendly during its lifetime. However, inaccurate data in the design phase would affect the ability of understanding and addressing these requirements. As

the uncertainty accompanies in processes of the product design, having accurate data is always a challenge.

To tackle the uncertainty in the design phase of a sustainable product, two approaches are presented in this chapter. The first approach is to evaluate and to adapt changes in the product design phase. The second approach looks for minimizing effects of measured changes on the product development time and environmental impacts. The approaches are elaborated in the following sections.

4.2 Evaluating effects of uncertainty on sustainable product design

The research seeks solutions for the variety across the future generation of a product known as the generational variety (Martin and Ishii; 2002). The change of customers' preferences during the product life cycle is uncertain in the product design stage. Due to the change of customers' preferences, a product may not satisfy customers' requirements anymore in the application stage. A solution is the product diversity, but it requires the additional cost and development efforts. Another solution, proposed in this research, is to evaluate changes and to adapt the changes in the product design phase. A design objective is therefore considered for minimizing product environmental impacts under customers' requirement change. For example, if the type of materials in a printer frame is identified as the most pollutant factor, the designer can replace the frame material to minimize environmental impacts of the printer. The proposed method provides a way to minimize product environmental impacts with the minimum cost.

The objective of the research is to investigate effects of the quantified changes in the design phase as measured in Chapter 3. The research contribution is an integrated method to

quantify and assess effects of the uncertainty on products. The proposed model is validated using a wheelchair product.

4.2.1 Proposed methodology to evaluate effects of uncertainty on product design

The proposed approach studies the environmental impacts of a product in the design stage considering the generational variety of the product. To evaluate the generational variety of a product, the changes of customers' preferences are simulated over a product life cycle as illustrated in Figure 4.1. In this figure, steps are shown in the numbered rectangular blocks and outputs are depicted using the dashed rectangular. Because the first step has been discussed in chapter 3, the proposed method is elaborated from the second step.

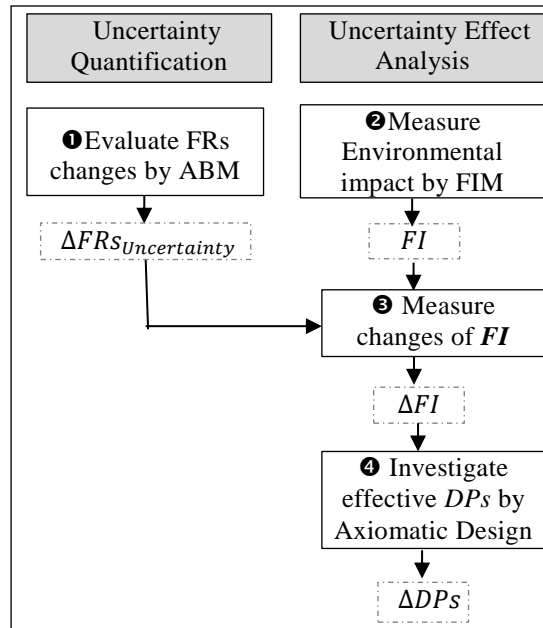


Figure 4.1 Methodology to evaluate uncertainty effects on environmental impacts of a product

The second step of the method measures environmental impacts of a product during the product life cycle. The Function Impact Method (FIM) is used in the evaluation of environmental impacts for individual product functionalities to connect next steps of the

method (Bernstein et al., 2010). The FIM evaluates the environmental impacts in a deterministic environment that are not affected by any uncertainty over the course of time. In the early design stage, knowledge and experience on the product environmental impacts are not as precise as expected. Devanathan et al. (2010) proposed to use the product Bill of Material (BOM) to investigate environmental impacts by benchmarking existing parts in the market. Therefore, the evaluation begins with decomposing a product into parts and elements, and then measures the material, manufacturing, use, and end of life impacts of each component. In the FIM, the functional contribution is measured using the contribution of each component on individual functions of a product. The evaluated environmental impacts of components are then divided into functions according to the functional contribution. The summation of the environmental impacts of product functionalities is calculated as Function Impact (FI).

In the third step, the effect of the changes in customers' preferences on environmental impacts of the product is measured. Hence, the analyses conducted in steps 1 and 2 are integrated into this step. This stage will build the link between the environmental impacts analysis and the generational variety of a product. The effect of users' preference changes over the product life cycle on environmental impacts is evaluated using Equation (4.1).

$$\Delta FI = \Delta FRS_{Uncertainty} * FI \quad (4.1)$$

To verify that the effects of uncertainty on the function impact (FI) are precisely measured, the changes of FRs ($\Delta FRS_{Uncertainty}$) should be normalized before using Equation (4.1). By the end of this step, a list of the most affected functional requirements over the

product life cycle is achieved. Such information is very useful in the early design phase; however, some arrangements are still required to use the information in product design.

In the last step, the contribution of each design parameter (DP) on environmental impacts of the product is investigated. A designer can use the results to design or redesign a product. Among mapping tools, the axiomatic design (AD) theory is utilized in this step. Our focus is on the physical domain where functional requirements (FRs) are mapped into design parameters (DPs). Two axioms including independence axiom and information axiom are evaluated. In the independence axiom, the independence of the functional requirements (FRs) is maintained. Here, functional requirements are defined as the minimum set of independent requirements that characterizes the design goal to minimize the environmental impacts. The information axiom aims to minimize design information content; the design with the least information content will be the best solution.

Two axioms are the tools used by a designer to search the optimum design based on design objectives. The independence axiom is used to ensure the decoupled or uncoupled design. Equation (4.2) indicates the relationship in a physical domain of the axiomatic design.

$$FRs = [A] * DPs \quad (4.2)$$

To provide an uncoupled or decoupled design, $[A]$ should be diagonal or triangular matrix respectively. The knowledge and experience of designers can be used to investigate appropriate DPs satisfying FRs independence as shown in Equation (4.3).

$$\Delta FI = [A] * \Delta DPs \quad (4.3)$$

In this step, we select proper DPs to satisfy related functional impacts (FI) to make $[A]$ a diagonal or triangular matrix. A designer may choose different sets of DPs or different array values within $[A]$ to satisfy an uncoupled or decoupled design; therefore, the second axiom is used to select the best design.

In real product design projects, the limitation in budget affects revising the entire product design. In this case, DPs should be prioritized according to the budget to optimize the design solution. We use the concept of Rigidity of Design Sustainability (\tilde{r}) to ensure that the maximum magnitude of environmental impacts is addressed under the available budget. Using a step-wised algorithm, the best DP with the maximum G value is selected. The G Index helps to choose the most pollutant DP to be revised using the least budget out of all DPs.

$$G = EI_i / RB_i \quad (4.4)$$

In each iteration (t), one DP out of n DPs is selected and \tilde{r} index is revised using Equations (4.5-4.6).

$$r_t = \sum_{i=1}^n EI_i - \sum_{i=1}^t EI_i \quad \forall t \leq n \quad (4.5)$$

$$\tilde{r} = r_t / \sum_{i=1}^n EI_i \quad (4.6)$$

The algorithm to search DPs stops when Equation (4.7) is satisfied. The required budget to design a component (RB_i) is estimated in these equations.

$$\sum_{i=1}^t RB_i \leq Total\ Budget \quad (4.7)$$

Efficiency of the proposed approach is discussed in the next section using the example of a real product.

4.2.2 Validation of the proposed approach

The proposed method is applied to a benchmarked wheelchair design. A sustainable solution is required for the wheelchair design to provide a balance among the product cost, durability, and low environmental footprints. The aim of this case study is to verify that the proposed method can help designers to improve environmental impacts of a product under generational variety uncertainty. All analyses are conducted for a benchmark wheelchair (Hosseinpour, 2013).

Initially, a customers' preference survey was conducted. The preferences were then mapped into functional requirements using QFD. A group of experts was contacted to discuss the mapping process and relationships of functional requirements and wheelchair components. After the QFD implementation, parameters related to the product life cycle and technology trends were estimated. If a product exists in the market, the past data are used for estimation; otherwise, similar technologies and products are benchmarked to obtain the parameters. Product behavioral and interactional functions are investigated using data mining and marketing research. It is important to know how customers would react when encountering a new technology. The customers' tendency to advertise a new technology after its adoption is investigated. Finally, the estimated parameters are used to simulate the product life cycle using agent-based modeling as described in Chapter 3. Agents are defined as customers' preferences that interact each other within an environment (market or city). The innovations of the technologies are updated and regularly broadcasted to all agents. Some pioneer agents may

adopt the new technology, and then advertise it through a group of connected friends. Through the simulation of the product life cycle, customers' preference changes are investigated over time.

Following the steps in Figure 4.1, the wheelchair life cycle is simulated using ABM. The parameters summarized in Table 4.1 are used for the life cycle simulation. Since the parameters and the nature of interactions are defined, any software package can be used to implement the proposed model; we use the AnyLogic commercial software package to simulate customers' preference changes.

Table 4.1 List of parameters used in ABM for the wheelchair life cycle simulation

Parameters	Value [unit]
Number of agents (I)	10,000
Number of parts (J)	20
Technology update time (P)	90 [day]
Product life cycle duration ($P_m(t_{mn})$)	20 [year]
Weight of media (innovation), (ω_{tech})	0.1 [%]
Weight of friends (imitation), (ω_{frd})	0.25 [%]
Number of FRs	17
Number of DPs	17

The model broadcasts new technology trends to random customers every 90-steps (equal to 90 days) to simulate three months. Then, those clients who follow the technology innovation are informed, and they may update their preferences. The trend of technology development is evaluated using the changes data of wheelchair parts during the last 20 years.

After the simulation of the wheelchair life cycle, measured changes in customers' preferences are transferred into changes in FRs ($\Delta FRs_{Uncertainty}$). The output is a list of the

normalized value of changes in FRs (to remove bias effects of data changeability) for measuring uncertainty effects. In the next step, the environmental impacts of the wheelchair during its life cycle are evaluated using the function impact method (FIM). The result is shown in Figure 4.2.

In Figure 4.2, the total environmental impacts index (EI) of each part is measured using the SolidWorks software package. Thus, the carbon footprint of each part is measured in a unit of kg carbon dioxide equivalent (CO_2). The environmental impacts measurements are conducted for stages of design, manufacturing, and end of life of a component. The next pace in the FIM is to distribute the contribution of components into the product functions. The weights (W) in Figure 4.2 are assigned based on experts' experience. The total environmental impacts of a component are then distributed over product functions to define the functional environmental impacts. The analysis highlights the most contributed functional requirements in environmental impacts of the wheelchair including having a moving system, supporting loads, and holding hip and thigh.

The effect of customers' preference changes on environmental impacts of the wheelchair is quantified using Equation (4.1). A change in rankings of FRs is observed when the effect of customers' preference changes on environmental impacts of the wheelchair is measured using Equation (4.8). Table 4.2 lists the rankings.

$$\Delta FI = \begin{bmatrix} 0.6 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 0.28 \end{bmatrix} \times \begin{bmatrix} 52.66 \\ \vdots \\ 3.91 \end{bmatrix} = \begin{bmatrix} 31.34 \\ \vdots \\ 1.10 \end{bmatrix} \quad (4.8)$$

Table 4.2 Comparing rankings of the FRs (the proposed method versus the FIM only)

List of FRs	Ranking of FRs	
	Proposed Method	The FIM
have a moving system	1	1
Hold hip and thigh	2	5
Support all loads without fracture	3	4
have Reclining back-rest, leg-rest	4	8
Hold the legs	5	9
Operate with electrical energy	6	11
Hold Hands	7	6
Does not tilt	8	3
Hold back body	9	2
Decline pressure point	10	7
Hold the head	11	10

Table 4.2 shows the influence of users' preference changes on the ranking of the most contributing FRs in wheelchair environmental impacts. Traditionally, decisions to revise the design of a product were made only upon life cycle of a product. The proposed method enriches the reliability of previous approaches by considering the effects of uncertainties. Despite the other methods, the developed method is integrated into the selection DPs using the AD as presented in Figure 4.3.

To identify the effective design parameters contributing to the environmental impacts of the wheelchair under uncertainty, the changes of *FI* are mapped into DPs. For an accurate solution, we applied the axiomatic design (AD) theory to provide uncoupled or decoupled design. As discussed in the literature, applying AD reduces the effects of uncertainty to specify design parameters that affect the functionality of a product.

Using the AD, the relationship between functional requirements and design parameters is depicted. The mapping illustrated in Figure 4.3 shows a decoupled design. The mapping area is divided into two main rectangular areas for specific mapping of parts, and the general design

parameters to simplify mapping process. If the Pareto rule is applied to decide DPs, the focus will be on investigating the DPs that contribute up to 70% of product environmental impacts. Within the first rectangular area, DPs are selected for the wheel, seat, main frame, and reclining mechanism. The second rectangular area lists some DPs to be considered for sustainable design of the wheelchair components including the social, environmental, and economic features. The DPs are the cost of components, number of components, material properties, component sizes, modular design of components, and component's service cycle.

Parts Vs. FRs	have a moving system		Operate with electrical energy		have Reclining back-rest, leg-rest		Hold Hands		Hold back body		Hold the head		Hold the legs		Hold hip and thigh		Support all loads without fracture		Does not tilt		Decline pressure point		Reduce the weight		Long service time cycle		Reduce number of components		Reduce the cost		Ease of reusing, recycling & remanufacturing		Reducing the environmental footprint and toxic material		Total EI	
	W	EI	W	EI	W	EI	W	EI	W	EI	W	EI	W	EI	W	EI	W	EI	W	EI	W	EI	W	EI	W	EI	W	EI	W	EI	W	EI	W	EI		
Base Frame		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0	0.8	11.0		0.0		0.0	0.1	0.7		0.0	0.1	0.7	0.1	0.7	0.0	0.3	0.0	0.3	13.8	
Anti-tip structure		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0	1.0	5.2		0.0		0.0		0.0		0.0		0.0		0.0		0.0	5.2	
Anti-tip wheel		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0	0.9	2.7		0.0		0.0		0.0	0.0	0.1	0.0	0.1	0.0	0.1	0.0	0.1	3	
Manual Wheel lock	1	0.2		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0	0.0	0.0		0.0	0.0	0.0		0.0	0.17	
Motor package		0.0	0.8	1.1		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0	0.1	0.1		0.0	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	1.36	
Hub-less, Drive wheel-rim 14"×3"	0.9	38.4		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0	0.0	1.1	0.1	2.3	0.0	1.1		0.0	0.0	1.1	0.0	1.1	45.15	
Drive wheel-pneumatic tire & tube	0.9	1.8		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0	0.0	0.1	0.1	0.1	0.0	0.1		0.0	0.0	0.1	0.0	0.1	2.11	
Front fork& caster	0.5	2.9		0.0		0.0		0.0		0.0		0.0		0.0		0.0	0.4	2.4		0.0		0.0		0.0	0.0	0.1		0.0	0.0	0.1	0.0	0.1	0.0	0.1	5.88	
Tire (solid tire foam inserted 8"×2")	0.9	9.4		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0	0.0	0.3	0.1	0.6	0.0	0.3		0.0	0.0	0.3	0.0	0.3	11.04	
Seat frame (fix seat 17")		0.0		0.0	0.2	9.0		0.0		0.0		0.0		0.0	0.5	22.4	0.2	9.0		0.0	0.1	2.2		0.0		0.0	0.0	1.1	0.0	1.1		0.0		0.0	44.83	
Seat cushion 16" x 17" x 2"		0.0		0.0		0.0		0.0		0.0		0.0		0.0	0.5	0.3		0.0		0.0	0.4	0.3	0.0	0.0		0.0		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.67	
Non folding back rest frame		0.0		0.0	0.4	4.1		0.0	0.5	5.2		0.0		0.0		0.0		0.0		0.0		0.0	0.0	0.3		0.0		0.0	0.0	0.3	0.0	0.3	0.0	0.3	10.35	
Back rest cushion 17"×18"×0.5		0.0		0.0	0.4	0.1		0.0	0.5	0.1		0.0		0.0		0.0		0.0		0.0		0.0	0.0	0.0		0.0		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.19	
Head rest-structure		0.0		0.0		0.0		0.0		0.0	0.9	1.8		0.0		0.0		0.0		0.0		0.0		0.0		0.0	0.0	0.1	0.0	0.1	0.0	0.1	0.0	0.1	2	
Headrest-pad (8" × 4.5")		0.0		0.0		0.0		0.0		0.0	0.9	0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.045	
Swing-away hanger 70 degree		0.0		0.0		0.0		0.0		0.0		0.0	0.8	3.5		0.0		0.0		0.0		0.0		0.0		0.0	0.1	0.2	0.1	0.2	0.1	0.2	0.1	0.2	4.4	
Footrest		0.0		0.0		0.0		0.0		0.0		0.0	0.7	6.1		0.0	0.1	0.9		0.0		0.0		0.0		0.0	0.1	0.4	0.1	0.4	0.1	0.4	0.1	0.4	8.7	
Adjustable Armrest structure		0.0		0.0		0.0	0.9	7.3		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0	0.0	0.2	0.0	0.2	0.0	0.2	0.0	0.2	8.14	
Armrest pad 14"		0.0		0.0		0.0	0.9	0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.035	
Battery- Amstron 12V / 34Ah		0.0	0.7	9.3	0.1	0.7		0.0		0.0		0.0		0.0		0.0		0.0		0.0		0.0	0.1	0.7	0.1	0.7		0.0	0.1	0.7	0.1	0.7	0.1	0.7	13.3	
	4	52.7	1.5	10.4	1.1	13.8	1.8	7.4	1.0	5.3	1.8	1.8	1.5	9.6	1.0	22.8	1.5	23.2	1.9	7.9	0.5	2.5	0.3	3.2	0.2	3.7	0.5	4.3	0.5	4.0	0.5	3.9	0.5	3.9		

Figure 4.2 Environmental impacts (EI) analysis based on component weight (W) in product function of the wheelchair

Functional Requirements	Design Parameters														ΔFI
	Wheels specification	Electrical Motor power	Reclining Mechanism	Arm-rest properties	Back-rest specification	Head-rest adjustability & comfort	Leg-rest property	Main frame strength	Anti-tip wheel mechanism	Material specification	Components' service cycle	Number of operational components	Cost of components	Modularity for EOL	
have a moving system	X														31.31
Operate with electrical energy	X	X													3.25
have Reclining back-rest, leg-rest			X												3.84
Hold Hands				X											2.78
Hold back body					X										1.99
Hold the head						X									0.69
Hold the legs							X								3.63
Hold hip and thigh								X							8.59
Support all loads without fracture								X							6.59
Does not tilt									X						2.27
Decline pressure point									X						0.71
Reduce the weight										X					1.03
Long service time cycle										X	X				1.21
Reduce number of components												X			2.94
Reduce the cost										X	X	X			3.96
Ease of reuse, recycling												X		X	2.65
Reducing environmental footprint												X		X	1.10

Figure 4.3 Mapping Functional Requirements (FRs) to Design Parameters (DPs) using Axiomatic Design theory

A comprehensive solution may need to redesign all components to minimize the environmental impacts of the product; however, the proposed algorithm chooses DPs to meet the minimum environmental impacts for the FRs based on the budget. To initiate assigning DPs, a list of given budget for each DP is needed; the budget should consider analyses and resources required for each DP. Because of the lack of data, an estimated budget is utilized based on the degree of coupling between DPs and the probability of changes for each DP. For more accuracy, some indexes are used to quantify design efforts for each DP as the indicator of required budget. Table 4.3 presents a list of criteria for the design activities that are indexes used by design experts for the wheelchair design. The criteria include the diversity of potential materials (C1), Variety of parts and details (C2), Coupling with the other parts (C3), Number of technical tests required (C4), Ease of access to developed technologies (C5), and

difficulties in prototyping (C6). All criteria are measured between 1 -10. A higher number reflects more efforts and budget needed to design a DP.

In Figure 4.4, the environmental impacts (EI) index is used to select DPs according to the estimated budget for DPs. The EI index is a normalized measure of functional impacts (ΔFI) for DPs in Figure 4.3. Figure 4.4 shows that by revising 5 DPs (DP1, DP8, DP9, DP7, and DP3) more than 85% of the product environmental impacts can be reduced. The developed method helps to prioritize the DPs according to the required budgets.

Table 4.3 List of the criteria to estimate design activities for DPs

No.	DPs	C1	C2	C3	C4	C5	C6	Sum
DP1	Wheels specification	4	4	3	5	5	4	25
DP2	Electrical Motor power	3	8	6	9	8	6	40
DP3	Reclining Mechanism	4	5	5	5	4	5	28
DP4	Arm-rest properties	4	4	4	4	4	5	25
DP5	Back-rest specification	5	6	4	5	4	4	28
DP6	Head-rest adjustability	4	5	4	4	5	4	26
DP7	Leg-rest property	4	5	3	5	5	3	25
DP8	Seat property	3	6	5	6	6	5	31
DP9	Main frame strength	7	8	8	7	6	6	42
DP10	Anti-tip wheel mechanism	3	5	5	4	4	3	24
DP11	Cushion specification	2	3	5	3	5	4	22

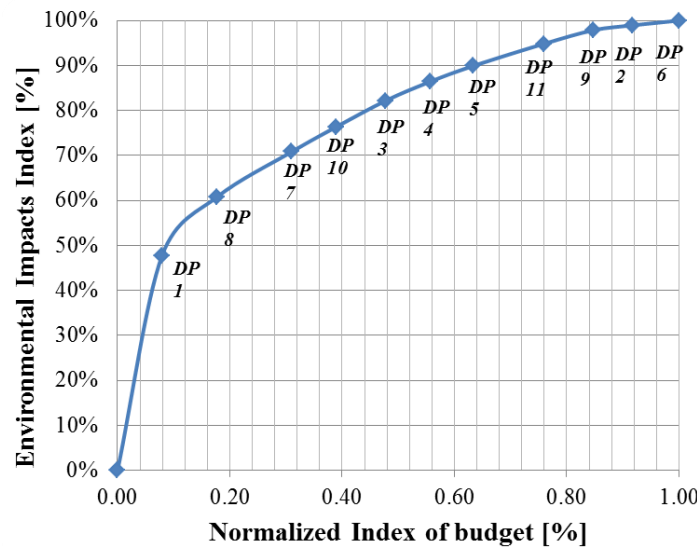


Figure 4.4 Prioritizing DPs to minimize the environmental impacts according to the normalized index of budget

The established DPs are then used to improve wheelchair's environmental impacts. The original design of the wheelchair can be revised considering general DPs identified in the small rectangular area (presented in Figure 4.3). Such improvements include reducing the weight of components, the number of components, and using environmentally friendly materials. Instead of end-of-pipe solutions, this research proposes a method to reduce environmental impacts before manufacturing and introduction of a product to the market. As presented in Table 4.4, a traditional analysis would direct us to identify the most pollutant components of a product, and improve its design for fewer impacts to the environment. On the contrary, this research measures the potential changes of a product in future. The design parameters (DPs) are then addressed for detail design improvements as a lack of existing methods. Therefore, a sustainable solution is obtained using the social (users' preference

mining), environmental (functional impacts analysis), and economic pillars (the budget or design efforts needed as a function of cost).

Table 4.4 Comparing proposed method with the traditional methods to improve product environmental impacts

	Traditional approaches	Proposed method
Used Analyses	-Components' environmental impacts	-Components' environmental impacts -Users' preference changes -Requested functional changes -Axiomatic design (resilient for changes)
Pollution Reduction Scope	-Product end-of-life	Entire product lifecycle including: -Design -Manufacturing -Product end-of-life
Benefits	-Identifies the most pollutant parts of a product	-Simulates/measures future functionalities of a product, and hints the design parameters to be improved.

4.3 Optimizing sustainable product design under uncertainty

Decisions made in the product design stage consist of several coupled and interdependent design tasks (Cho and Eppinger, 2005; Sapuan et al., 2006). The interdependencies among design decisions form multiple search iterations in the design process. Design iterations in the solution search increase the product design cost and time, it is essential to reduce the design iterations.

Users' requirement is dynamic in the competitive market. Changes in users' preferences happen in the product life cycle, as a surge of information affects design tasks leading to

more search iterations in the design process. Any internal or external disturbances such as technology evolution and changes in users' preferences will influence the stability of a design solution. The stability is defined as the ability of a design process to reduce the volume of work within all design tasks to a reasonable solution in a finite number of search iterations. The resource allocation needs to be revised to obtain design decisions efficiently. By allocating more resources to individual tasks in the design, the entire design process expedites to reach the desired solution.

Methods based on the design structure matrix (DSM) can map the complex engineering design problems (Steward, 1981). The ability of DSM to present the interdependencies of design tasks has made these methods popular in design processes (Yassine and Braha; 2003). Several extensions of these methods such as the work transformation matrix (WTM) have been presented (Smith and Eppinger, 1997). The DSM has been adopted rapidly to reduce the design time. In addition, the WTM transforms the design process as a vector-matrix model similar to the modeling method in the modern control engineering theory. As a result, problems, such as iterations in coupled design tasks, modeled by the WTM can be dynamically analyzed using control engineering methodologies. This conclusion is approved when the control theory was applied in many aspects of production systems to understand the dynamic behavior of these systems (Duffie et al., 2014). However, there is a lack of research to consider multiple objectives for the coupled design task. Particularly, the combination of mathematical optimization methods and the modern control theory has not been applied to the design problem. This research bridges the gap in the literature by proposing the optimization models considering the cost and environmental impacts in the product development process.

This research searches a cost-effective and environmentally friendly solution for reduced design lead time in a dynamic design environment considering changes in users' preferences. Several generations of a product may be introduced during its life cycle by revising the product design. As a result, some products may face either to be redesigned into a new product or to be revised to meet the new need. Obviously, it is desired to address user requirements with the minimum cost and time. Therefore, the research objectives are first to assess effects of the unexpected disturbances on product design, and then to propose a method to search an optimum solution considering the minimum cost and environmental impacts.

4.3.1 Proposed methodology to optimize sustainable product design under uncertainty

The proposed method models product design decisions under uncertainties in three stages as shown in Figure 4.5. Uncertainties are defined as changes in users' preferences for a product during its life cycle. There are several methods to measure changes in the users' preferences such as design for variety (Martin and Ishii; 2002), agent-based modeling (Afshari et al., 2013), and Big Data analytics (Afshari and Peng, 2015a). The proposed method assesses effects of quantified uncertainties on the product design process.

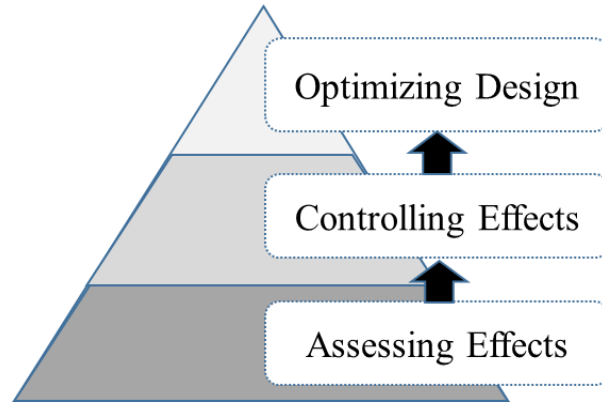


Figure 4.5 Stages of the proposed methodology for a design process under uncertainty

The method describes ways to assess and control effects of uncertainties on the design process. Since the extended models based on automatic control engineering cannot cope with the desired optimal solution, mathematical programming is applied in the sustainable product design.

State-space representation of the design process

As some design parameters (DPs) are interrelated to each other, a change in a DP imposes a rework to the other DPs. In this case, several iterations and design loops are required in the design process. In each iteration, values of DPs are revised to reduce the remaining work in a design process. Therefore, the amount of work in each iteration depends on the remained amount of work in the previous stage and effects of analysis on each stage. This resembles the concept of the state-space representation in control engineering in Equation (4.9). The index of the discrete time variable (f) denotes a finite number of iterations.

$$\mathcal{X}(f + 1) = \mathcal{A}\mathcal{X}(f) \quad (4.9)$$

In Equation (4.9), $\mathcal{X}(f)$ is a work vector consisting of n coupled design tasks to be completed. Matrix \mathcal{A} (work transformation matrix) represents the information dependency between tasks. Thus, the work vector in iteration $f + 1$ is measured using Equation (4.9) that is an open-loop state-space representation or homogenous state-space system (HSS). When all design tasks are completed in a finite number of iterations, the design project is called stable. The stability of an open-loop control system is measured using the eigenvalue of matrix \mathcal{A} . The HSS does not consider external disturbances of a system, only initial conditions matter for its response in each iteration. However, in a real system, the existence of external disturbances is inevitable. Therefore, a non-homogenous state-space system (NHSS) can better reflect real systems. Two types of expected and unexpected disturbances are assumed for a system. Unexpected disturbances may include changes in user requests or failures to address those requests properly by designers, which conclude to the interruption or delay of a design process (Ogata, 1995). Such changes in design requirements as a disturbance in a dynamic system can be compensated by more iterations of the design process before reaching to stable conditions. This adaptability to handle unexpected disturbances in the design phase needs less cost and time compared to other methods such as redesigning the entire product. In addition, the advantage of considering unexpected disturbances in the design process is to ensure satisfying new requirements with the minimum iterations and resources. Equation (4.10) presents a modified model that considers unexpected disturbances or changes.

$$\mathcal{X}(f + 1) = \mathcal{A}\mathcal{X}(f) + \mathcal{B}\mathcal{W}(f) \quad (4.10)$$

Matrix \mathcal{B} is defined as Disturbance Transformation Matrix (DTM), and $\mathcal{W}(f)$ is the disturbance input in iteration f due to unexpected external events (Ogata, 1995). Because \mathcal{W} is a function of iterations, the system can consider disturbances in each iteration by setting non-zero elements in \mathcal{W} matrix. Each item in $\mathcal{W}(f)$ represents the additional rework imposed by random events to design tasks.

There is another type of disturbances, which needs extra resources to minimize design loops as shown in Equation (4.11).

$$\mathcal{X}(f + 1) = \mathcal{A}\mathcal{X}(f) + \mathcal{C}\mathcal{U}(f) \quad (4.11)$$

Equation (4.11) denotes that the amount of work to be done by a design task is a linear combination of work created by other coupled design tasks in the previous iteration plus the effect of control inputs. The input matrix \mathcal{C} represents the proportion of common resources shared by two or more tasks. If resources are not shared among the various tasks, matrix \mathcal{C} is considered as a unit matrix. Vector $\mathcal{U}(f)$ describes the additional resources that each task needs to reach the desired state. Thus, the elements of matrix \mathcal{U} denote the additional resources (e.g., overtime work, new methods, new staff, new technologies) to reduce the amount of rework. The unit of elements in matrix \mathcal{U} can be selected as cost, time, volume of work, number of design actions.

The state feedback control proposed by Lee et al. (2004) applies an appropriate state feedback gain matrix (K) to achieve the desired stability of a system. In our method, elements

of the matrix K denote the degree of controls applied by one task on other design tasks. Thus, the input control in Equation (4.11) is represented as follows:

$$\mathcal{U}(f) = -K\mathcal{X}(f) \quad (4.12)$$

Equation (4.12) can be substituted in Equation (4.11), and considering matrix \mathcal{C} as I (unit matrix), the closed-loop control system is obtained using Equation (4.13).

$$\begin{aligned} \mathcal{X}(f+1) &= (\mathcal{A} - IK)\mathcal{X}(f) \\ &= \mathcal{A}^*\mathcal{X}(f) \end{aligned} \quad (4.13)$$

The stability of a closed-loop state feedback system depends on the eigenvalues of matrix \mathcal{A}^* . Since values of elements in matrix K are effective in the eigenvalues of matrix \mathcal{A}^* , finding the appropriate matrix K is essential for a stable system.

Finally, if the system is accompanied by expected and unexpected input controls, the volume of work will be measured using Equation (4.14) (Golnaraghi and Kuo, 2010). Figure 4.6 represents the model structure of a closed-loop feedback system based on Equation (4.14).

$$\mathcal{X}(f+1) = \mathcal{A}\mathcal{X}(f) + \mathcal{B}\mathcal{W}(f) + \mathcal{C}\mathcal{U}(f) \quad (4.14)$$

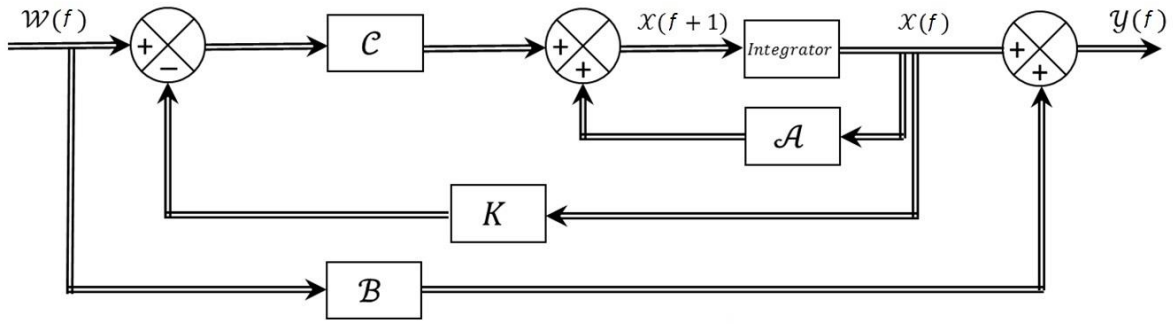


Figure 4.6 The structure of a closed-loop feedback system model based on Equation (4.14)

In Figure 4.6, $\mathcal{W}(f)$ represents the unexpected disturbance exerted to the system as a result of changes in users' preferences. Matrix \mathcal{B} is defined to apply a direct effect of the disturbance on the design process. For simplicity, matrix \mathcal{B} can be substituted by I (unit matrix). Matrix K , as a feedback gain matrix, regulates the disturbances caused by $\mathcal{W}(f)$ and \mathcal{A} . If the state of the system at iteration k , $(\mathcal{X}(f))$, deviates from a desired state, the matrix K can be used to deal with the deviation. Moreover, the stability of the design process depends on the eigenvalues of the state-space representation that is $(\mathcal{A} - K)$. This shows the importance of matrix K in reaching a desired amount of design tasks in the minimum number of iterations.

The quantified uncertainty as an unexpected disturbance is applied in the first iteration of the design process. It is assumed that the initial amount of work, $\mathcal{X}(f = 0)$, is an n -vector with elements equal to 1. Using Equation (4.10), the volume of work required finishing all design tasks are updated. Hence, matrix $\mathcal{X}(f = 0)$ is updated, and the value of the element will be either more than or equal to 1. This extension helps to apply effects of the quantified uncertainty on a design process. As a result of applying uncertainties in the model, the design

process will reach a stable state with more iterations. Because the uncertainty is only applied to the design process in the first stage of a design process, values of elements in \mathcal{W} matrix are equal to zero for the rest of iterations. By embedding $\mathcal{W}(f \geq 1) = 0$ in Equation (2), the equation denotes an open-loop design process in Equation (4.9). Continuing the design process using Equation (4.9) does not help to control effect of uncertainties on the number of iterations. Therefore, some adjustments are applied in the model.

In order to control effects of uncertainties, an updated matrix $\mathcal{X}(f)$ is used to serve as $\mathcal{X}(f = 0)$ in Equation (4.11). The adjustment in the model includes defining a desired state of the system to reach (Lee et al., 2004). In other words, a desired number of iterations to finish all design tasks (f_D) should be targeted at this stage. Elements of the desired state matrix $\mathcal{X}(f_D)$ are set as a ratio of the initial matrix $\mathcal{X}(f = 0)$. A ratio of 0.1 means that a design task is considered as complete if the remained amount of work is equal or less than 0.1 (Ong et al., 2003; Huang and Chen, 2006). However, the ratio can be reduced close to zero for more accurate result.

Based on the control engineering, the number of iterations in a design process can be reduced if more resources are assigned to design tasks in each iteration. Equation (4.13) uses this concept to compensate the reduced number of iterations by adding more resources in matrix $\mathcal{U}(f)$. Thus, the aim is to find the best value of matrix K . Fortunately; there are several methods to calculate matrix K as the trade-off between time and resources (Lee et al., 2004; Ogata, 1995). Consequently, effects of uncertainties are controlled by adding more resources to each design task within individual iterations.

Description of the optimization model in a design process

The real design always has limitations in budget and resources. In addition, there are constraints of regulations and environmental concerns for the resources allocation. Thus, the constraints and regulations do not allow to control effects of uncertainties by adding more resources to the design task. The goal is to optimize the number of iterations in a design process under uncertainties considering different objective functions.

Model 1: Cost Minimization

The cost optimization aims to find the number of iterations as decision variables to minimize the total design cost. The mathematical model of the problems is presented as follows:

$$\min \mathcal{Z}_1 = \sum_{f=1}^{I_{opt}} \mathcal{C}\mathcal{J}_i y_i + \sum_{j=1}^J \mathcal{C}\mathcal{R}_j * \sum_{f=1}^{I_{opt}} \sum_{k=1}^K U_{kij} \quad (4.15)$$

Subject to:

$$\sum_{f=1}^{I_{opt}} y_i = 1 \quad (4.16)$$

$$\sum_{j=1}^J \sum_{f=1}^{I_{opt}} \sum_{k=1}^K U_{kij} \leq R_j \quad \forall i \in I, k \in K \quad (4.17)$$

$$I_{opt} \geq \sum_{f=1}^{I_{opt}} f * y_i \quad (4.18)$$

$$y_i \in \{0,1\}, f \in \text{integer} \quad (4.19)$$

Where:

\mathcal{CJ}_f = cost of iteration f within a design process,

\mathcal{CR}_j = unit cost of resource j used to compensate time,

U_{kfj} = amount of resource j used within iteration f for task k ,

R_j = available units from resource j in the design process,

I_{max} = the maximum number of iterations,

I_{opt} = the optimum number of iterations ($I_{opt} \leq I_{max}$),

In this model, Equation (4.15) is the objective function to minimize the total design cost including cost of iterations and cost of resources. Variable I_{opt} in the second term of Equation (4.15) regulates the cost of resource allocation up to the optimum number of iterations. Equation (4.16) denotes that only one optimum iteration should be selected by the model. Equation (4.17) shows that resources assigned to design tasks (k) in each iteration (f) should not exceed the available resource (j). Equation (4.18) decides the best number of iterations among all feasible iterations up to I_{max} . Types of variables are defined in Equation (4.19).

Model 2: Environmental Impacts Minimization

The goal of the second model is to minimize the total environmental impacts of a design process by finding the number of iterations as the decision variable. Since the constraints are similar to the first model, the objective function is described in Equation (4.20).

$$\min \mathcal{Z}_2 = \sum_{f=1}^{I_{opt}} y_i^* \sum_{k=1}^K \sum_{j=1}^J U_{kfj} \mathcal{P}_{kj} / \sum_{f=1}^{I_{opt}} \sum_{k=1}^K (1 - X_{kf}) \quad (4.20)$$

In this equation, \mathcal{P}_{kj} denotes the pollution (e.g., CO₂ emissions) from each unit of resource j ; therefore, the objective is to minimize the total pollution caused by the design process because of resources used such as new methods, new staff, and new technologies. By increasing iterations, the total environmental impacts of the design process are increased. In addition, the total amount of work done by tasks are increased; hence, the aim is to minimize the fraction in Equation (4.20) by finding the optimum number of iterations. The parameter X_{kf} denotes the total work done by task k in iteration f .

Solution approach

The solution approach proposed for the optimization problem is presented as an algorithm in Figure 4.7. The algorithm assesses effects of uncertainties by updating $\mathcal{X}(f = 0)$ using Equation (4.10). $\mathcal{X}(f = 0)$ refers to the amount of remained work before the design process initiates. The objective function regulates the goals to be satisfied in the optimization problem. After deciding the objective function, the homogenous state-space model presented in Equation (4.9) is used to reach a predefined level of remained amount of work. The value of remained amount of design tasks can be set to any number between 0.1 to 0.01 meaning 10% to 1% of $\mathcal{X}(f = 0)$. In the literature, 0.1 is used by researchers; however, for a more accurate design process, one may use 0.01 as the value of remained amount of design tasks. Thus, the maximum number of iterations (I_{max}) without an extra resource allocation is obtained. The value of parameter I_{max} is influential in the model because it defines a limit for the calculations. The rest steps in the algorithm are conducted for a discrete interval of iterations as $[1, I_{max})$.

The state-space gain matrix (K) and the vector $\mathcal{U}(f)$ are required as parameters in the optimization model. These values are determined using Equation (4.11). An optimization model is formulated based on the computed values in each iteration. In other words, the best value of the objective function is decided after solving $I_{max}-1$ mathematical models.

Two conditions are defined to ensure the optimal objective function (Z). First, the optimum number of iterations in each model (I_{opt}) has to be equal to the iteration number (f). If the mathematical model decides $I_{opt} < f$, it proves that the selected f is not optimum. Secondly, the value Z is the best among all other objective function values measured within $[1, I_{max})$. Finally, the model reports the optimum number of iterations (I_{opt}^*) considering the objective and constraints.

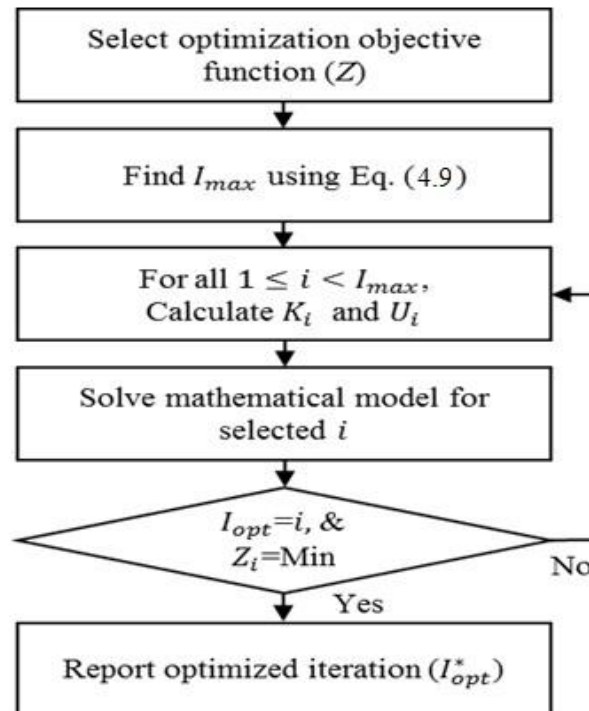


Figure 4.7 The proposed solution approach for the optimization model

4.3.2 Validation of the proposed approach

The development of a smartphone is used as an example to verify the proposed method. The effect of changes in users' preferences as uncertainties on the design process is evaluated.

The design process of a smartphone includes multiple dependent and independent tasks. Such dependency in design tasks causes rework and iterations in the design process. Using the work transformation matrix (WTM), the dependencies are measured. Figure 4.8 presents the WTM for a smartphone.

From (j) \ To (i)		A	B	C	D	E	F	G
Data transfer	A	0	.9	.3	.1	0	0	.3
Internet-connectivity	B	.6	0	.1	.3	0	0	0
Software	C	0	0	0	.1	0	0	.1
Battery	D	0	0	.1	0	.1	.1	.3
Cameras	E	0	0	.1	.3	0	.1	0
Outer facing	F	0	0	0	0	0	0	0
Physical Interfaces	G	0	0	.1	.6	0	.1	0

Figure 4.8 WTM for the smartphone

For the smartphone, the coupled design tasks are selected to be analyzed in Figure 4.8. In the WTM, each element a_{ij} ($i \neq j$) reflects the amount of work in a unit created for task i if a unit of task j is completed. Diagonal elements are equal to zero. If an initial work vector, $\mathcal{X}(f)$, is available, the work vectors in next iterations are obtained using Equation (4.9). For the smartphone, elements of $\mathcal{X}(f)$ are assumed as 1 that shows 100% of the design

work is remained to be completed in the design process. All eigenvalues of the matrix presented in Figure 4.8 are between -1 and +1 as a sign that the entire design project will converge to its completion. Moreover, the greatest eigenvalue belongs to the task A that means it needs more iterations than the other tasks to finish a design process.

Another important issue in the design phase is the effect of changes in user preferences. Users have shown a variety of requirements for a smartphone during its life cycle. Since several generations of the smartphone have been introduced to the market, changes in user preferences have been reflected in the next generation. We assume that the changes in user preferences are available as proposed by Afshari and Peng (2015b), but the effects of quantified changes are not identified. Thus, the work vector is revised to include disturbances $\mathcal{W}(f)$ using Equation (4.10). In this case, $\mathcal{W}(f)$ affects the process at $f = 0$ for set \mathcal{B} as a unit matrix. The measured work vector is presented in Equation (4.21).

$$\mathcal{X}(f + 1) = \mathcal{A}\mathcal{X}(f) + \mathcal{B}\mathcal{W}(f) \quad (4.21)$$

$$= \begin{bmatrix} 0 & 0.9 & \dots & 0 & 0.3 \\ 0.6 & & & & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & & & 0 & 0 \\ 0 & 0 & \dots & 0.1 & 0 \end{bmatrix} \times \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 1 & 0 & \dots & 0 & 0 \\ 0 & & & & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & & & 0 & 0 \\ 0 & 0 & \dots & 0 & 1 \end{bmatrix} \times \begin{bmatrix} 0.75 \\ 0.35 \\ \vdots \\ 0.54 \\ 0.34 \end{bmatrix} = \begin{bmatrix} 2.35 \\ 1.39 \\ \vdots \\ 0.54 \\ 1.14 \end{bmatrix}$$

The updated amount of work $\mathcal{X}(f)$ after the change of users' preferences is used to measure the eigenvalue, eigenvector, and gain matrix. Equations (4.12-4.13) measure controlling features of the smartphone design process based on desired iteration numbers. A task is considered to be completed when the remained amount of work is less than 10% of the initial work. Thus, I_{max} is measured when no excessive resources are added to expedite the design process using the homogenous presentation of the state-space representation. For the

smartphone, the design tasks converge to the desired amount of work in 12 iterations ($I_{max} = 12$). Table 4.5 summarizes the amount of work in each iteration. The desired number of iterations is then set to obtain the amount of extra resources to meet desired iterations. Measured numbers are used as parameters of the proposed mathematical models for optimizing design iterations. It is assumed that the used resources in the design process are new materials and technologies.

Table 4.5 The amount of work in each iteration

Tasks	Iterations											
	1	2	3	4	5	6	7	8	9	10	11	12
A	2.02	1.82	1.43	1.13	0.86	0.64	0.48	0.36	0.27	0.20	0.15	0.10
B	1.72	1.40	1.17	0.91	0.69	0.53	0.39	0.29	0.22	0.16	0.12	0.09
C	0.18	0.11	0.06	0.03	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
D	0.58	0.22	0.14	0.06	0.03	0.01	0.01	0.00	0.00	0.00	0.00	0.00
E	0.36	0.19	0.08	0.05	0.02	0.01	0.01	0.00	0.00	0.00	0.00	0.00
F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
G	0.55	0.37	0.14	0.09	0.04	0.02	0.01	0.01	0.00	0.00	0.00	0.00

Based on the iPhone components (Nadadur et al., 2012), a BOM of the iPhone is built. The BOM and a list of manufacturing processes are used to conduct the environmental impact analysis. Environmental impact analysis is conducted using SimaPro8 (PRé Consultants, 2015) known as the state-of-the-art software for the life cycle assessment and environmental impact analysis (Devanathan et al., 2010). A summary of the environmental impact analysis for the parts is presented in Table 4.6. Only physical components with a potential to measure the environmental impacts are selected; components such as “operating system” and “software” were not selected for the analysis.

To design new products, companies such as the Apple spend lots of money as presented in Figure 4.9. However, because obtaining accurate data for the research and development

Table 4.6 The environmental impact analysis for the selected parts in iPhone using PRé Consultants (2015)

<i>Tasks</i>	<i>Environmental impacts (\mathcal{P}_{kj}) [kg CO_2]</i>
A	4.27
B	4.27
C	4.27
D	40.20
E	10.14
F	25.74
G	11.10

Cost	Iteration normalized cost [\$]											
	1	2	3	4	5	6	7	8	9	10	11	12
\mathcal{CI}_i	26	20	15	11	8	6	4	3	2	2	1	1
\mathcal{CR}_1							104					
\mathcal{CR}_2							26					
\mathcal{CR}_3							6.5					

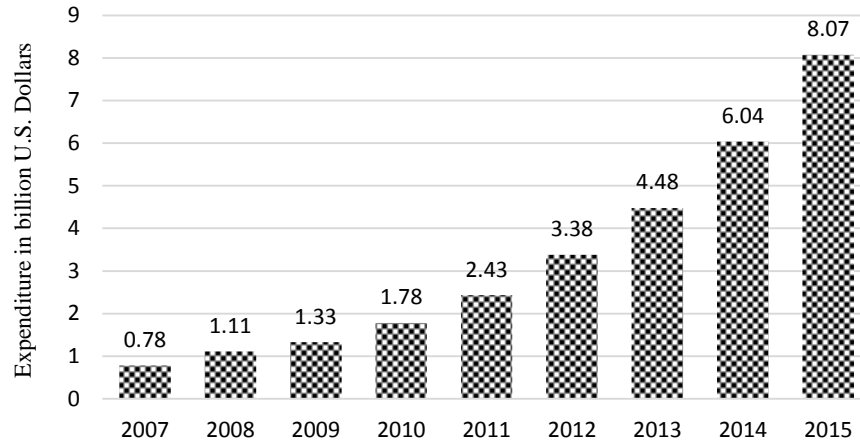


Figure 4.9 The Apple expenses for Research and Development (R&D) (Statista, 2016)

4.3.3 Analysis and discussion

The proposed approach for the design process of the smartphone is coded using MATLAB. The disruption of changes in users' preferences is added as the input of control problem. The objective function values for different iteration numbers are measured using the first and second models. Besides the optimization of iterations using the proposed model, effects of uncertainties on the objective function values are analyzed. The models are then solved, and objective function values are determined.

For the first objective function (the cost minimization), the presented solution approach in Figure 4.7 is used for three cost scenarios in Table 4.7. In addition, each cost scenario is utilized to solve deterministic and uncertainty models. The results show that the first model with uncertainties reaches to the minimum value of the objective function at the 5th iteration. It means that using extra resources (material) to expedite the design process is cost-efficient when the desired amount of work is set for the 5th iteration. In reality, it is confirmed that

The solution approach in Figure 4.7 requires checking the validity of results. As discussed before, a solution is valid if the optimum number of iterations is equal to the iteration number ($I_{opt} = f$); otherwise, the minimum cost value is not acceptable. Table 4.8 summarizes the cost objective values and conducted validity test. The results confirm the 5th iteration as the optimum and valid cost value.

Table 4.8 The analysis of objective function values for the cost model with uncertainty

		Iterations											
		1	2	3	4	5	6	7	8	9	10	11	12
Optimum iteration	1	1											
	2		1										
	3			1									
	4				1								
	5					1							
	6						1						
	7							1					
	8								1				
	9									1	1		
	10												
	11											1	1
	12												
First cost scenario (\mathcal{CR}_1)	Objective Value	373	282	180	77	60	157	259	363	468	574	678	784
	Validity	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✗
Second cost scenario (\mathcal{CR}_2)	Objective Value	112	85	56	27	21	43	67	93	118	145	170	196
	Validity	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✗
Third cost scenario (\mathcal{CR}_3)	Objective Value	47	36	25	15	11	15	19	25	31	37	43	49
	Validity	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✗

To evaluate effects of the cost scenarios on the optimization results, the cost optimization model is solved using deterministic and uncertain data. If all cost scenarios provide similar result, it is concluded that the optimal iteration number is independent of the fractions in Table 4.8. The outcomes of the cost minimization model are depicted in Figure 4.10.

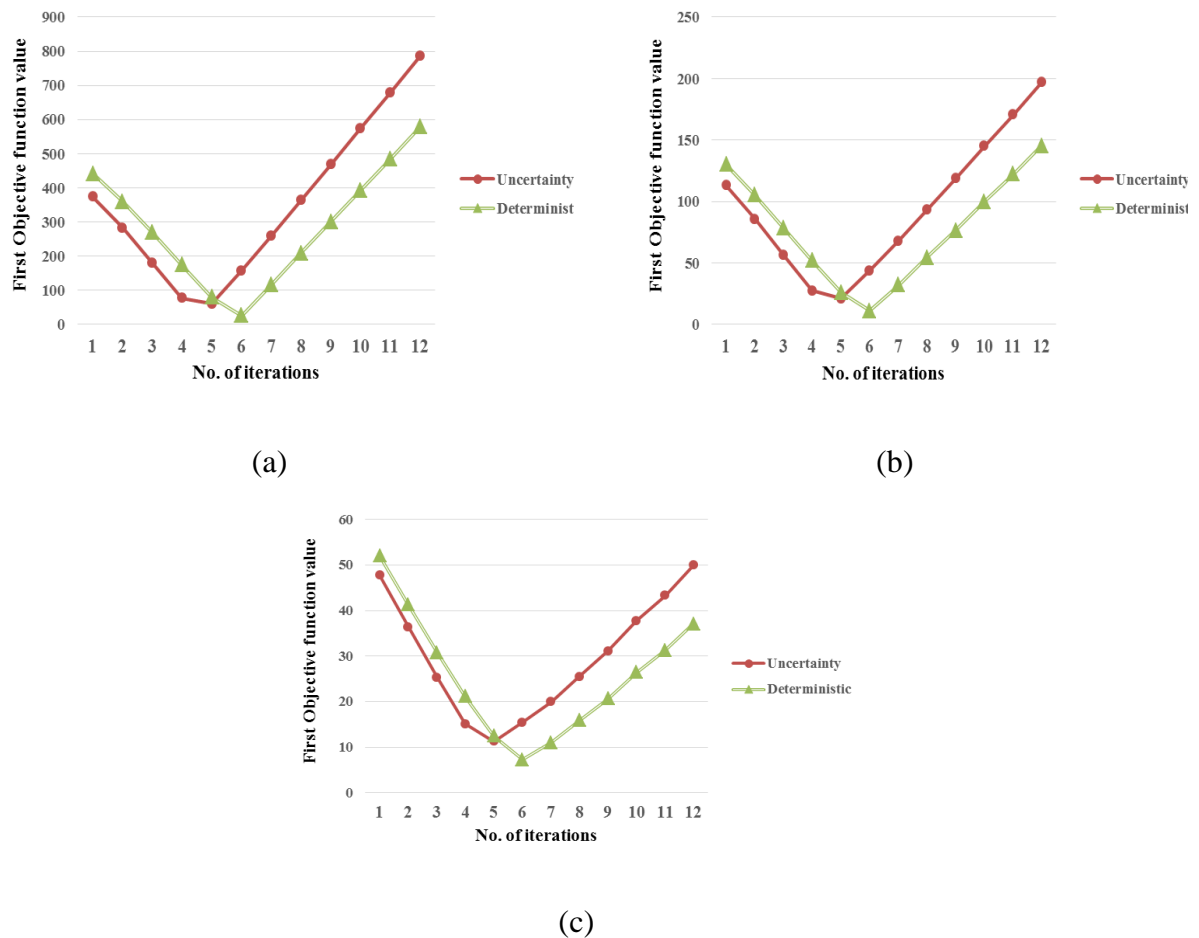


Figure 4.10 The objective function values for the cost minimization model using (a) first cost scenario, (b) second cost scenario, and (c) third cost scenario

Although different cost scenarios are used, the model determines the 5th iteration as optimum for the uncertain data, and the 6th iteration as optimum for the deterministic data. Thus, the cost scenarios do not influence the optimum number of iterations.

Similar analysis is conducted for the second objective function (the environmental impacts minimization). By applying uncertainty in the model, the best objective function value is reached at the 5th iteration as presented in Table 4.9. The model is solved using the deterministic data as well (see Table 4.10).

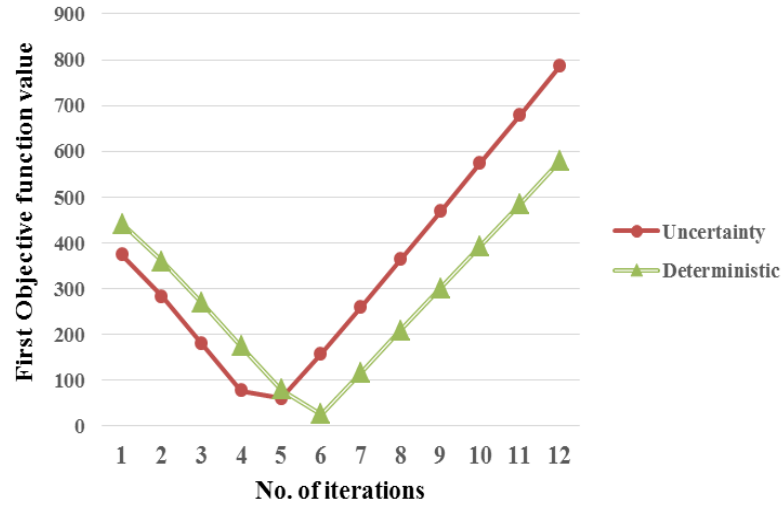
Table 4.9 The objective function values and validity test for the second model with uncertainty

Optimum iteration	Iterations											
	1	2	3	4	5	6	7	8	9	10	11	12
1	1	1	1			1						
2												
3												
4				1								
5					1							
6												
7							1					
8								1				
9									1			
10										1		
11											1	
12												1
Objective Value	173	147	120	65	49	167	329	527	762	1031	1337	1678
Validity	✓	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	✓

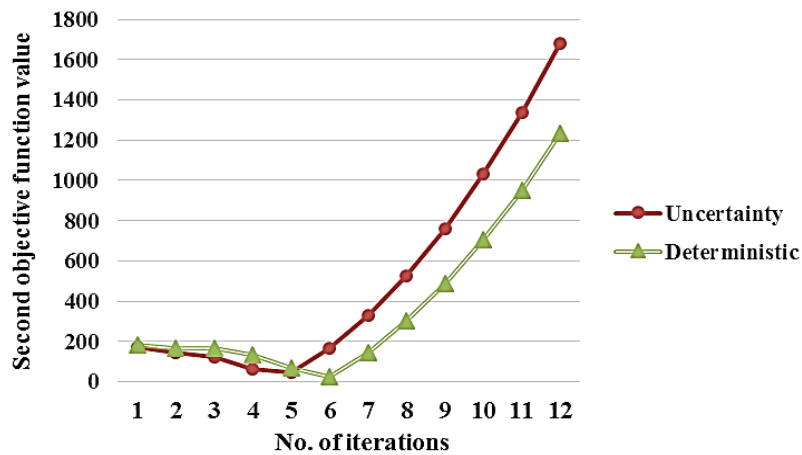
Table 4.10 The objective function values and validity test for the second model without uncertainty

Optimum iteration	1	2	3	4	5	Iterations						
	6	7	8	9	10	11	12					
1	1	1	1				1					
2												
3												
4				1								
5					1							
6												
7							1					
8								1				
9									1			
10										1		
11											1	
12												1
Objective Value	182	169	165	132	70	23	147	302	487	705	953	1232
Validity	✓	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	✓

Next analysis is the evaluation of effects of uncertainties on objective function values. Therefore, both models are used to measure the optimum number of iterations including and excluding effects of changes. As shown in Figure 4.11 (a), the excluding uncertainty for the first model shifts the optimum iteration to the sixth iteration. Moreover, the total cost of the optimum iteration is less than the process that considers the uncertainty.



(a)



(b)

Figure 4.11 Objective function values for models including and excluding uncertainties

For the second model, some iterations fail to meet conditions in Figure 4.7. Thus, the optimum iteration is 5 since iteration 6 fails validity in the proposed solution approach. In other words, the second model suggests a different iteration as optimum ($I_{opt} \neq i$). Therefore, if the design search is set to the end at the 5th iteration, it will meet both objective

functions. The result is significant in the reduction of the cost and environmental impacts compared to 12 iterations as the less resource usage.

In conclusion, the presented models could significantly minimize the total cost of a design using the optimum number of iterations. Also, the result is significant in the reduction of the environmental impacts compared to 12 iterations as the lower resource usage. The proposed methods help to distribute workloads and allocate resources during design task planning when unexpected disturbances happen. For companies such as the Apple that has spent enormously on research and development for new products, the proposed methods can provide huge savings in terms of cost and environmental impacts.

The research conducted in this Chapter has been published in the following journal and conference proceedings:

- Afshari H, Peng Q, Gu P. Design Optimization for Sustainable Products under Users' Preference Changes. *The ASME Journal of Computing and Information Science in Engineering*. 2016; 16(4):041001-7. doi:10.1115/1.4033234.
- Afshari H, Peng Q, Gu P. Reducing Effects of Design Uncertainties on Product Sustainability. *Cogent Engineering*. 2016. doi:10.1080/23311916.2016.1231388.
- Afshari H, Peng Q, Gu P. Effects of Design Uncertainties on Product Sustainability. *Proceedings of the International Conference on Innovative Design and Manufacturing (ICIDM)*. 2016. Auckland, New Zealand.

Chapter 5

Multi-objective Design of Sustainable Systems under Uncertainty

5.1 Introduction

This chapter extends the scope of sustainable product design into sustainable system design. An eco-industrial park (EIP) is a venue for businesses and local communities to cooperate to increase economic gains while minimizing environmental impacts of products and processes (Chertow and Lifset, 2004). The process of involving separated industries in a collective approach is called Industrial Symbiosis (IS). The aim is to utilize the competitive advantage in collaborations and the synergies (physical exchange of materials, energy, water, and by-products) stemming from geographic proximity (Chertow, 2000). This definition directly refers to the concept of a circular economy within an industrial area, where a goal of

the zero waste needs to be reached. Indeed, by minimizing environmental impacts, symbiotic relations have to be increased to maximize the resources recycling within the EIP (Boix et al., 2015).

Despite numerous research on material exchanges (e.g., water treatment) in EIPs, there is a modest number of publications dealing with the energy exchange between units, and even lesser on thermal energy networks. Figure 5.1 presents a schematic view of a single industry including the energy generation facility and processes.

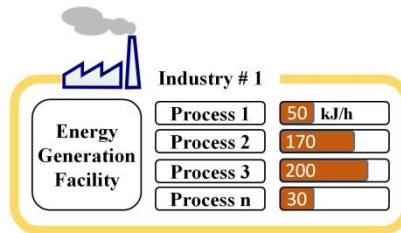


Figure 5.1 Schematic view of a single industry

The best flow exchanges among a cluster of industries are decided to design industrial symbioses. A challenge is that a designer may comprise versatile goals in the symbioses design. Besides economic objectives, symbioses are created to minimize environmental impacts of flow exchanges. A schematic view of exchanges between industries is presented in Figure 5.2.

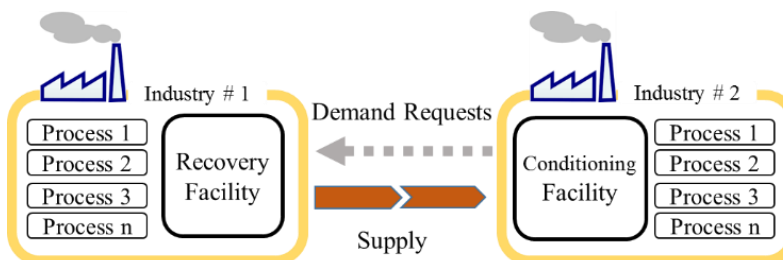


Figure 5.2 Schematic view of industrial symbioses

Another major challenge is the need to consider uncertainty in the IS design. To design a network of symbioses, numerous data are required. However, studies have addressed the lack of access to data as a common challenge to model symbioses (Boix et al., 2015). Designing synergies under uncertainty is an approach to overcome the limitation in data.

The goal of this research is to optimize industrial symbioses networks for a cluster of industries considering economic and environmental objectives. Thus, a mixed integer linear programming model is developed to optimize the location and capacity of flow exchanges between industries under uncertainties. A solution approach is then applied to deal with uncertain data during optimization. The research contributions include: (i) considering technical features in the modeling of energy demand and supply, (ii) proposing a multi-objective model for the minimization of the total annual cost and pollutions, (iii) presenting different perspectives to the energy symbioses models and investigating effects of these perspectives on the optimal solution, and (iv) considering uncertainties in the modeling and solution approach to bridge the gap of the literature.

5.2 Modeling symbioses in eco-industrial parks for versatile perspectives

Before introducing the proposed method, it would be beneficial to state the problem in this research. Each factory can supply the required energy within its own facility or purchase from external resources. Depending on the type of a process, different amount of the extra/unused/wasted energy could be recovered. A local energy generation, particularly heat production, is expensive and with pollution for the environment. Instead, the required energy can be supplied either through a supply network or through a line from another process that produces the extra heat to match the need properly.

To establish energy symbioses for a set of industries, some infrastructure investments are required. The investments are for heat exchange networks (HENs) and pipelines to transfer energy between firms. Obviously, industries review economic objectives before contributing to an energy symbiosis. Figure 5.3 demonstrates the networks of industries before and after energy symbioses.

As shown in Fig. 5.3 (b), although industry #3 may demand to establish symbioses with industry #1, some technical or economic concerns prohibit this symbiosis. Maximizing the number of energy symbioses should reflect the technical feasibility of solutions. The more reasonable features are included in the model, the more feasible symbioses can be achieved.

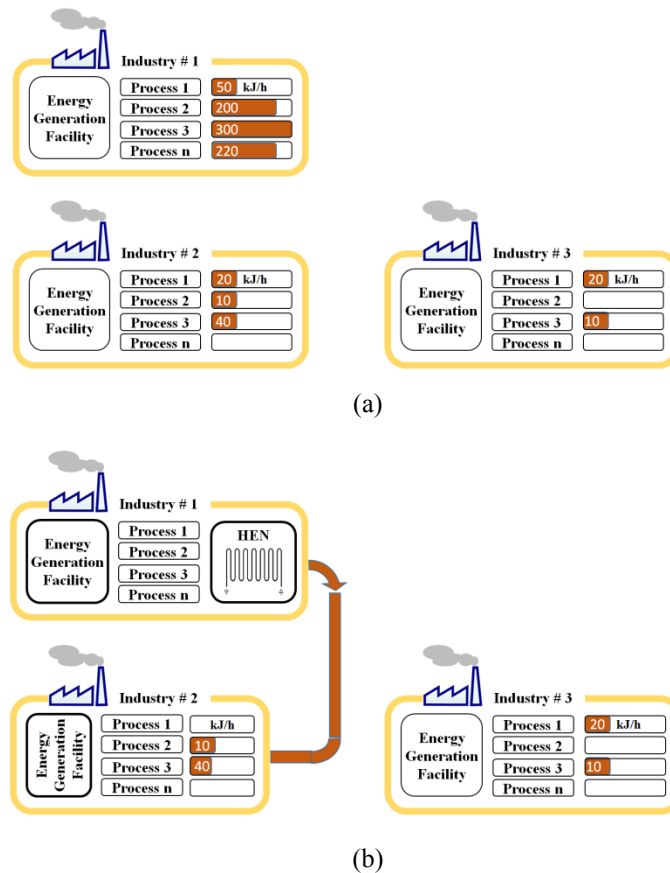


Figure 5.3 Industries (a) before and, (b) after energy symbioses

Sets, parameters, and variables of the proposed model are listed as follows:

Sets,

- I Set of supplier industries
- J Set of demand industries
- K Set of energy types

Parameters,

- D_j^k Demand of industry j from energy type k
- S_i^k Supply of industry i from energy type k
- L_{ij}^k Distance of industry i and j for energy network k
- U_{ij}^k Unit cost of network between i and j for energy k
- CD_j^k Fixed cost of generating energy within industry j
- CC_{ij}^k Fixed cost of conditioning energy from industry i to j
- CE_{ij}^k Selling price of energy k from industry i to j
- CI_j^k Variable cost of generating energy within industry j
- RC_{ij}^k Cost of recovering energy k for industry j in i
- TC_j^k Tax on carbon for energy k imposed to industry j
- TS_i^k Tax saving of industry i by exporting energy k
- α_{ij}^k Depreciation rate of pipeline between i and j
- β_{ij}^k Depreciation rate of facilities between i and j
- γ Distance limit for industries to build synergies
- TMP_i^k Temperature of energy k supplied by i
- TMP_j^k Temperature of energy k demanded by j

Variables,

- x_{ij}^k Percentage of demand supply from i to j for energy k
- y_{ij}^k Binary variable if symbioses exists between i and j

The first objective function maximizes the energy symbioses between industries. Because variable x_{ij}^k is defined as the independence of energy demands, this objective encourages flow exchanges between industries as presented in Equation 5.1.

$$\text{Max } Z_1 = \sum_{k=1}^K \sum_{j=1}^J \sum_{i=1}^I x_{ij}^k \quad (5.1)$$

The second objective function minimizes the total annual cost of establishing energy symbioses networks between industries. Since the perspective analysis requires different terms to be included in the cost objective function, two separated objective functions are defined for energy buyers' (Equation 5.2) and EIP managers' (Equation 5.3) perspectives.

$$\min Z_2 = \sum_{k=1}^K \sum_{i=1}^I \sum_{j=1}^J CD_j^k \beta_{ij}^k y_{ij}^k + \sum_{k=1}^K \sum_{j=1}^J CI_j^k D_j^k (1 - \sum_{i=1}^I x_{ij}^k) + \quad (5.2)$$

$$\sum_{k=1}^K \sum_{j=1}^J \sum_{i=1}^I CC_{ij}^k \beta_{ij}^k y_{ij}^k - \sum_{k=1}^K \sum_{j=1}^J \left(TC_j^k D_j^k \sum_{i=1}^I x_{ij}^k \right)$$

$$\min Z_3 = \sum_{k=1}^K \sum_{i=1}^I \sum_{j=1}^J CD_j^k \beta_{ij}^k y_{ij}^k + \sum_{k=1}^K \sum_{j=1}^J CI_j^k D_j^k (1 - \sum_{i=1}^I x_{ij}^k) + \quad (5.3)$$

$$\sum_{k=1}^K \sum_{j=1}^J \sum_{i=1}^I (U_{ij}^k L_{ij}^k \alpha_{ij}^k + CC_{ij}^k \beta_{ij}^k) y_{ij}^k + \sum_{k=1}^K \sum_{i=1}^I \sum_{j=1}^J RC_{ij}^k D_j^k x_{ij}^k -$$

$$\sum_{k=1}^K \sum_{j=1}^J \left(TC_j^k D_j^k \sum_{i=1}^I x_{ij}^k \right) - \sum_{k=1}^K \sum_{i=1}^I (TS_i^k \sum_{j=1}^J D_j^k x_{ij}^k)$$

In Equation 5.2, annual fixed and variable costs of generating energy within buyers' firms are added to the annual cost of conditioning centers embedded inside the firms. If the demanded energy is not supplied by external sources, the energy generation facility generates unsupplied amount of the energy demand. It is assumed that the supplied firm includes piping and HEN costs in the selling price (CE_{ij}^k); therefore, the buyer may only purchase conditioning centers at its own firm. Because a part of the demand is supplied by external sources, its tax saving is reduced from the total cost.

From EIP managers' point of the view, all annual costs should be considered for the cost minimization objective; therefore, Equation 5.3 adds some costs of suppliers including costs for piping network, energy recovery facilities at suppliers, and tax saving for the recovered energy.

The third objective function minimizes the environmental impacts of symbioses in industries as presented in Equation 5.4. Because the pollution of recovered by-product/ waste/ energy is less than the supplying raw material/ energy ($PE_{ij}^k < PI_j^k$), Equation 5.4 motivates flow exchanges in industries.

$$\min Z_4 = \sum_{k=1}^K \sum_{i=1}^I PE_{ij}^k \sum_{j=1}^J D_j^k x_{ij}^k + \sum_{k=1}^K \sum_{j=1}^J PI_j^k D_j^k (1 - \sum_{i=1}^I x_{ij}^k) \quad (5.4)$$

Constraints are categorized for the effect of perspectives as well. The constraints for the buyers' side optimization are as follows:

$$\sum_{i=1}^I x_{ij}^k \leq 1 \quad \forall k, j \quad (5.5)$$

$$D_j^k x_{ij}^k \leq S_i^k \left(1 - \left(\frac{TMP_j^k}{TMP_i^k} \right) \right) y_{ij}^k \quad \forall k, i, j \quad (5.6)$$

$$\sum_{j=1}^J \frac{D_j^k x_{ij}^k}{(1 - (TMP_j/TMP_i))} \leq S_i^k \quad \forall k, i \quad (5.7)$$

$$\begin{aligned}
CI_j^k D_j^k \sum_{i=1}^I x_{ij}^k + TC_j^k D_j^k \sum_{i=1}^I x_{ij}^k - CD_j^k \sum_{i=1}^I \beta_{ij}^k y_{ij}^k \\
> \sum_{i=1}^I CE_{ij}^k D_j^k x_{ij}^k \quad \forall k, j
\end{aligned} \tag{5.8}$$

$$(L_{ij}^k - \gamma) x_{ij}^k \leq 0 \tag{5.9}$$

$$x_{ij}^k \leq y_{ij}^k \tag{5.10}$$

$$0 \leq x_{ij}^k \leq 1, y_{ij}^k \in \{0,1\} \tag{5.11}$$

Constraint 5.5 refers to satisfy up to 100% buyers' energy demand. Constraints 5.6 and 5.7 balance demand and supply equations between industries. Constraint 5.6 demonstrates that in terms of temperature, the energy capacity of a supply firm should be enough to be selected for supplying demanded energy. Constraint 5.7 highlights that the total supplied demand should not exceed the supply capacity of an industry. Constraint 5.8 ensures that each energy buyer pays less money when contributing to energy symbioses than it supplies all demand within the firm. In other words, only financially feasible symbioses are selected in the model. Constraint 5.9 seeks for industries within a specified distance limit to build synergies. Constraint 5.10 checks if energy is supplied from selected industries for symbioses. Constraint 5.11 defines variable types in the model.

Constraint 5.12 checks if an individual investment for each energy symbioses (the piping and recovery cost) is economical for the network. Investments should be reimbursed by selling the recovered energy in a defined time period.

$$CE_{ij}^k D_j^k x_{ij}^k > (U_{ij}^k L_{ij}^k \alpha_{ij}^k + CC_{ij}^k \beta_{ij}^k) y_{ij}^k + RC_{ij}^k D_j^k x_{ij}^k \quad (5.12)$$

$$-TS_i^k D_j^k x_{ij}^k \quad \forall k, i, j$$

For the heat required for each industry, constraints 5.6-5.7 are defined. As presented in Figure 5.4, temperature is an important parameter to identify the heat supplied for each firm (Bergman and Incropera, 2011).

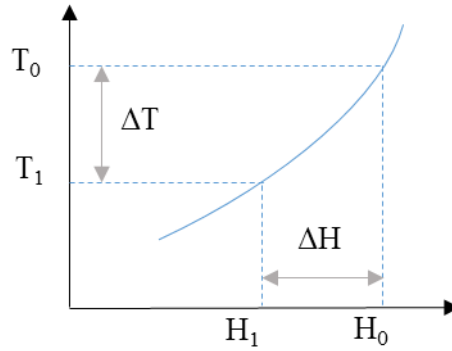


Figure 5.4 Relations between temperature and enthalpy

For the heat demand of a firm, the required energy follows Equation 5.13:

$$\dot{E} = \dot{m} c_p \Delta T \quad (5.13)$$

The total heat transfer power (\dot{E}) is measured as a function of the fluid flow rate (\dot{m}), heat capacity (c_p), and temperature change. By assuming a perfect process, the fraction η of the supplied heat (from a to b) is measured as shown in Equation 5.14 (Giedt, 1971). Thus, the total heat transferred to an industry is measured as presented in Equation 5.15.

$$\eta = \frac{T_a - T_b}{T_a} \quad (5.14)$$

$$E_b = \eta E_a = \left(1 - \frac{T_b}{T_a}\right) E_a \quad (5.15)$$

5.3 Multi-objective design of symbioses under uncertainty

The optimization problem in a simplified form is for a set of stakeholders (including industries) interested in the synergy creation; we are looking for the best flow exchange (named symbioses) considering economic and environmental measures. Since uncertainty can affect the optimal decision of symbioses and the further selection of future partners, it is necessary to assess effects early in the method. In addition, there is a need to select partners under the formulated uncertainty. Figure 5.5 depicts the framework of the proposed method in a step by step manner.

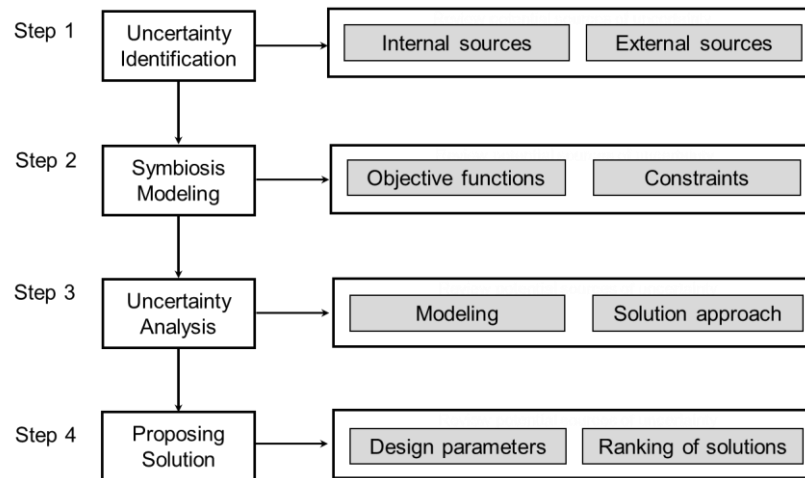


Figure 5.5 Steps for the optimal design of industrial symbioses under uncertainty

To identify uncertainties, internal and external sources are investigated. As presented in Table 5.1, the demand uncertainty and supply uncertainty are selected as internal uncertainties.

If a supplier fails to fulfill its customers' demand, such failure affects customers' activities. To minimize the impacts, the supply uncertainty as well as the demand uncertainty should be considered in the symbioses network design.

Table 5.1 Uncertainties identified to model for industrial symbioses optimization

Uncertainty	Type	Definition
Demand/Supply	Internal	Any drastic variation in predefined values of demand/ supply
Supply Price	Internal/ External	Any change either internal or external that makes other supply sources more interesting
Tax on carbon	External	Reduction/ increase in Tax on carbon due to national/ international regulations

The similar consideration should be taken into account for uncertainty in the supply price and tax on carbon. If other supply sources (other than industrial symbioses) provide lower prices, industries would revise their ties with current industry partners. For tax on carbon, it is expected to increase for a short term, but any reduction in the tax rate would impact established symbioses.

After modeling symbioses as presented in section 5.2, uncertainties should be embedded in the model. There are several models to deal with uncertainty in a model. Using the stochastic optimization, deterministic values of parameters are substituted by statistics of decided uncertainties. Therefore, the new objective functions are formulated as follows:

$$\min Z_1 = \mathbb{E}(f_1(\xi(D_j^k), \xi(CI_j^k), \xi(TC_j^k))) \quad (5.16)$$

$$\min Z_2 = \mathbb{E}(f_2(\xi(D_j^k))) \quad (5.17)$$

For example, Equation 5.4 is revised as Equation 5.18.

$$\begin{aligned} \min \mathcal{Z}_2 = & \sum_{s=1}^S P_s * (\sum_{k=1}^K \sum_{i=1}^I P E_{ij}^k \sum_{j=1}^J \xi(D_j^k) x_{ij}^k + \\ & \sum_{k=1}^K \sum_{j=1}^I P I_j^k \xi(D_j^k) (1 - \sum_{i=1}^I x_{ij}^k)) \end{aligned} \quad (5.18)$$

Therefore, Equations 5.3-5.12 should be revised as well to include uncertain parameters in the model.

As the solution approach, a sample average method (SAM) is applied to handle the stochastic nature of the model by estimating the objective functions. Because the most popular way to deal with randomness in a model is to optimize the expected value of an arbitrary function of parameters, we can rewrite the objective functions as shown in Equation 5.19 (Gutjahr and Reiter, 2010). Such arbitrary function of parameters should be defined over an appropriate probability space.

$$\frac{1}{N} \sum_{v=1}^N f_{\theta}(x, \omega_v) \approx \mathbb{E}(f_{\theta}(x, \omega)) \quad (5.19)$$

In this equation, N random and independent scenarios are used to approximate objective function values. Each scenario reflects randomness by ω_v , where $v = (1, 2, \dots)$ represents stochastic parameters. Using an estimation of the expected value of functions, the stochastic optimization model is changed to a deterministic one that is relatively easier to be solved. Thus, the multi-objective model is simplified as presented in Equation 5.20.

$$\min \left(\frac{1}{N} \sum_{v=1}^N f_1(x, \omega_v), \frac{1}{N} \sum_{v=1}^N f_2(x, \omega_v), \dots \right) \quad (5.20)$$

Since a weighted method is applied to solve the multi-objective model, an algorithm to solve the model is used. First, the model is solved using a single objective. The values are used to normalize the weighted multi-objective function. The multi-objective model is then solved, and results are stored. The process continues up to testing all desired weights. Because of using the sample average method, all described steps are followed for a new set of uncertainty scenarios. Finally, solutions are evaluated to decide the desired network topography.

5.4 Case study

The proposed models have been applied to optimize energy symbioses using anonymized data inspired by a set of industries in France. Figure 5.6 demonstrates the location of industries involved to investigate the possible energy symbiosis.

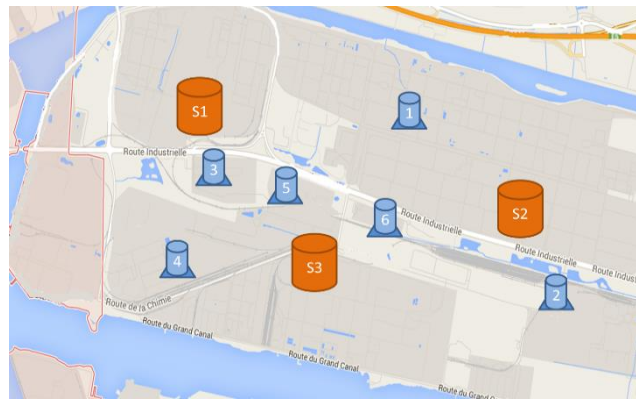


Figure 5.6 Map of anonymized industries to investigate possible energy symbioses

The objective is to find the optimal energy exchange flows between industries considering technical and economic constraints. Moreover, the optimum network should motivate more exchanges to reduce the fuel consumption for economic and environmental purposes. Tables 5.2-5.4 present the details of studied industries.

Table 5.2 Distances (KM) between industries in the studied area

Suppliers	Buyers					
	1	2	3	4	5	6
S1	8	17	2	7	4	6
S2	14	2	11	13	7	4
S3	10	8	5	3	3	4

Table 5.3 Energy specification of industries in the studied area

Energy specs.	Suppliers			Buyers					
	S1	S2	S3	1	2	3	4	5	6
Heat (Ton/yr.)	90	70	100	35	25	10	70	60	30
Temperature (K)	673	523	473	403	373	443	403	423	383

Table 5.4 Major parameters included in the models

Parameter	Unit	Value
Depreciation period of pipelines	Year	20
Depreciation of facilities (e.g., HEN)	Year	10
Interest rate	%	5
Heat recovery cost	€/kWh	0.028
Heat price generated from gas	€/kWh	0.06
Gas pollution rate	kg CO ₂ / kWh	0.063
Tax on carbon	€/kWh	0.0042

The proposed models are applied to minimize the total annual cost and environmental impacts of the network considering maximized energy symbioses. The models are formulated in AIMMS optimization package. Using a 4 GB RAM, 2.0 GHz PC, the AIMMS could solve the problem in less than one second.

5.4.1 Perspective analysis for modeling symbioses in EIPs

For two perspectives including energy buyers and EIP managers, two separated models are formulated. In this regard, the first two objective functions are modeled in the AIMMS. Figure 5.7 depicts the optimal solution for each model. In this figure, each energy buyer is connected to particular energy supplier. The selection of connections is based on the minimum annual costs and maximum percentage of demand supply.

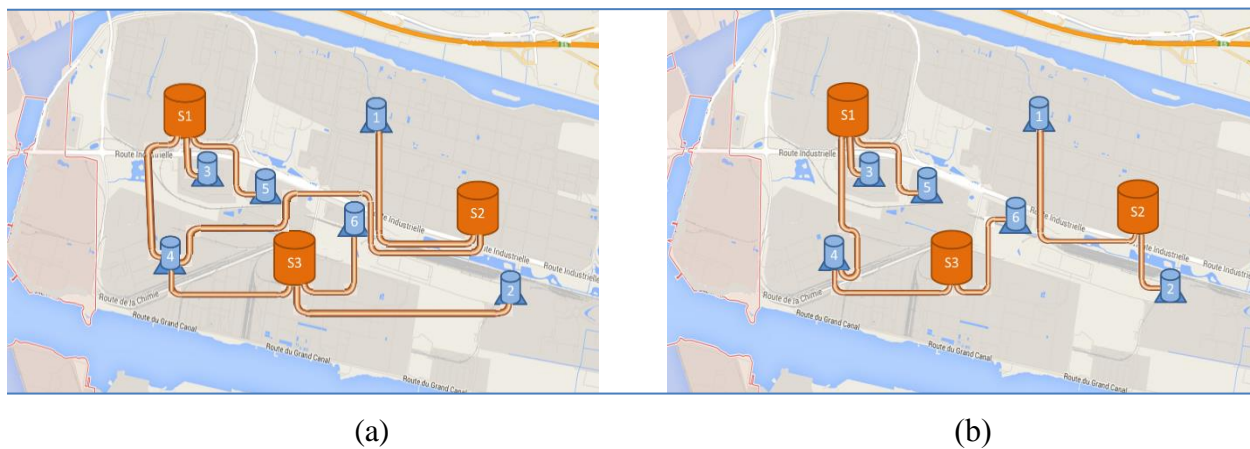


Figure 5.7 Energy symbioses network for (a) buyers' perspective, (b) EIP managers' perspective

Besides the schematic presentation of optimized connections, two energy symbioses networks are compared using indexes presented in Table 5.5. The indexes compare the cost and the length of optimized network for each perspective.

Table 5.5 Comparing two energy symbioses networks

Indexes	Buyers	EIP managers
Total annual cost [€]	48,932,363	47,404,740
Suppliers' cost [€]	47,791,414	44,472,370
Buyers' cost [€]	1,140,949	2,932,370
Length of pipeline [km]	45	26

The indexes show that the optimization model based on buyers' perspectives would increase the total annual cost of symbioses. However, the buyers' cost would be decreased up to 2.5 times more than the second network. Because the piping cost is included in the second model (EIP managers' model), shorter energy flows have been selected than the first one. Moreover, a more detailed analysis is conducted to investigate the efficiency of each network. The analysis looks for the efficiency and sensitivity of optimal networks under presented scenarios. The efficiency measures are described as follows:

Demand Satisfaction (DS): This measure identifies the percentage of buyers' demand covered in each model. Although each buyer would like to maximize this index, some technical or economic constraints could reduce its value. Similar weighted index can be applied to measure values of the demand satisfaction. The indexes are measured using Equations 5.21 and 5.22.

$$DS_j = \sum_{i=1}^I x_{ij} \quad j = 1 \text{ to } 6 \quad (5.21)$$

$$WDS_j = \sum_{i=1}^I D_j x_{ij} / \sum_{j=1}^J D_j \quad j = 1 \text{ to } 6 \quad (5.22)$$

Supply Utilization (SU): The ideal condition for a supplier is to sell the entire recovered heat to consumers. Therefore, the ability of a model to utilize the maximum capacity of suppliers is measured as presented in Equation 5.23. The index is also useful to estimate suppliers' ability for future network extension. A very close index value to 0 is the sign of network inefficiency. In the contrary, an index value near 1 represents networks brittle state for demand fluctuations. Thus, a middle point between [0, 1] boundaries is as an ideal value.

$$SU_i = \sum_{j=1}^J D_j x_{ij} / S_i \quad i = 1 \text{ to } 3 \quad (5.23)$$

Carbon Tax Reduction (CTR): This measure addresses environmental impacts of models to minimize the amount of CO₂ used for the energy generation. A higher value of the index means the better performance of the model. Because the EIP model assesses tax saving for all industries, only the tax saving from buyers' side is used to compare the models.

$$CTR = \sum_{j=1}^J \left(TC_j D_j \sum_{i=1}^I x_{ij} \right) \quad (5.24)$$

Supply Capacity under Demand Uncertainty (SCDU): The measure investigates the ability of energy suppliers to cover demand fluctuations. Due to unknown nature of variations in energy demands, the measure reflects the flexibility of an established symbioses network to cover demands. To assess the measure, energy demands have been simulated to quantify demand variations. The suppliers' capacities are then evaluated to deliver the accumulated demand. Table 5.6 shows the evaluated measures to compare the effect of the perspectives.

Table 5.6 Efficiency measures for symbioses networks

Indexes	Buyers	EIP managers
DS	(1,1,0.73,1,1,1)	(0.8,1,1,1,1,1)
WDS	99%	97%
SU	(0.63, 0.48, 0.42)	(0.63, 0.53, 0.38)
CTR	6,273,223	6,153,462
SCDU	(0.68, 0.48, 0.47)	(0.66, 0.48, 0.43)

Since suppliers in both models have a higher capacity than the total demand, technical features (e.g., temperature) and economic measures (e.g., pipeline cost) govern the partner

selection. Comparing the DS and WDS indexes shows that the first model could serve demands more than EIP managers' model. As expected, buyers' perspective model promotes greater energy symbioses. However, differences of indexes between two models are not significant. Similar results are demonstrated for SU and CTR indexes to conclude that buyers' model has presented a better performance.

For the last efficiency measure, the existing demand of buyers has been increased by 30%. The results show that the topography of the first model (buyers' perspective) will not change, while the second model requires revising the network structure. This means that the EIP managers' model is not resilient to demand variations. Therefore, the managers may decide to select buyers' perspective for a stable performance over demand variations and other efficiency measures.

5.4.2 Studying the effect of uncertainty on optimal symbioses network

Table 5.7 presents the uncertain parameters. The uncertain data in the model are defined using a range or statistical distribution. In each scenario, a sample from bounded space/distribution function is obtained for modeling. In this table, the demand and supply declared in a normal distribution refers to the current value presented in Table 5.4.

Table 5.7 Uncertain parameters included in the models

Parameter	Type	Data
Demand	Distribution	Normal (Demand, δ_j)
Supply	Distribution	Normal (Supply, δ_i)
Supply Price	Range	[0.054, 0.063]
Tax on carbon	Range	[0.0042, 0.01]

To analyze the effect of objective functions on the solution, each objective function is applied separately. The objective functions include minimization of the total annual costs of

the network and minimization of the total environmental impacts of the network. Using a weighting method, the multi-objective model is then solved and the solutions are compared. To provide a comprehensive analysis of the all stakeholders, the models are formulated for EIP managers' perspective. Figure 5.8 presents the physical view of the optimized synergy networks using single and multiple objectives. The multi-objective model and cost minimization model provide a similar network structure. Arrows in Figure 5.8 show the direction of the flow from suppliers ($i=3$) to buyers ($j=6$).

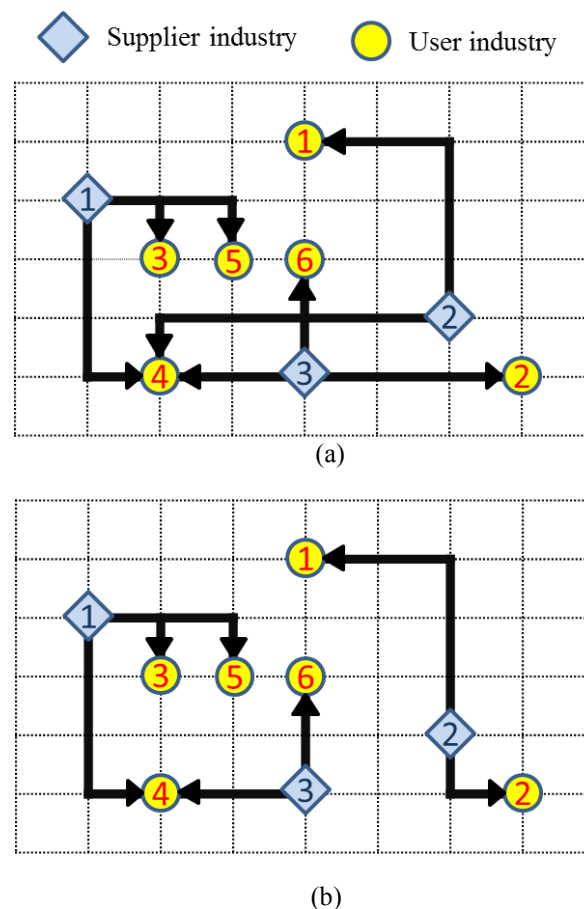


Figure 5.8 Optimized symbioses networks using (a) the minimization of environmental impacts, (b) the minimization of the total cost, and the multi-objective model

The models are compared using indexes presented in Table 5.8. The indexes include individual objectives functions. Moreover, the length of a pipeline is used to compare the models on required pipeline networks. Because both the multi-objective model and total cost minimization provide a similar network structure, the indexes are presented together.

Table 5.8 Comparing optimized symbioses networks using single and multiple objective functions

Indexes	Min environmental impacts	Min total cost & Multi obj.
Total pollution [kg co ₂]	90,910,655	91,309,860
Total cost [€]	48,932,363	47,404,740
Pipeline [km]	45	26

The indexes show that the model for the environmental impacts minimization gives the lower pollution compared to other models. In contrast, the other models could save more cost compared to the model for the environmental impacts minimization.

The effects of the uncertainties are evaluated using the weighted multi-objective model. Equal weights are assigned to both cost minimization and environmental impacts models. The sampling average method is used to solve the multi-objective model. The objective function values are estimated based on average values of scenarios generated using Table 5.7. Each uncertain parameter is assessed separately to clarify its effects on the model.

Demand uncertainty: This uncertainty originates from the expansion of industries that ends to more raw material/energy consumption. It is assumed that each industry can increase its demand up to 50%. After generating $N=10$ scenarios, the multi-objective model is solved and the results are evaluated. The liability of flow exchanges between suppliers and users is decided based on the number of confirmed connections and average amount of the supply. To

compare effects of the demand uncertainty, results of a deterministic multi-objective model are presented as well in Figure 5.9.

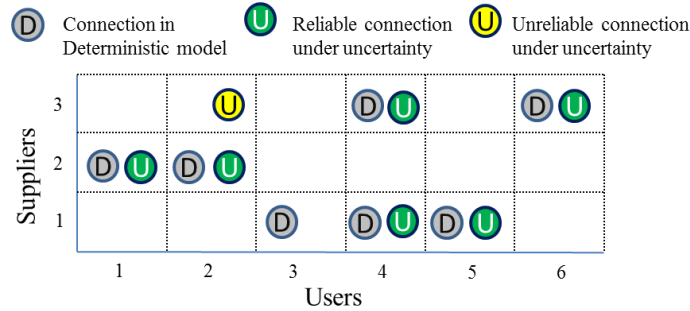


Figure 5.9 Comparing effects of the demand uncertainty on the optimized flow exchanges in the multi-objective model

As Figure 5.9 presents, no supplier can satisfy the demand of user 3 under the demand uncertainty. Also, supplier 3 is considered to supply the demand of user 2, but the connection will be established for a sever increase in demand. Other flow exchanges remain unchanged.

Supply uncertainty: If a supplier cannot support the promised supply, the user will miss a required demand. In this case, a user may prepare its material/energy from other sources. It is assumed that each supplier may decrease its supply up to 50%. The multi-objective model is solved using 10 generated scenarios. Similar to the demand uncertainty, the number of confirmed connections and the average amount of supplies are used to decide liability of flow exchanges. The effects of the supply uncertainty are evaluated using the deterministic multi-objective model as presented in Figure 5.10.

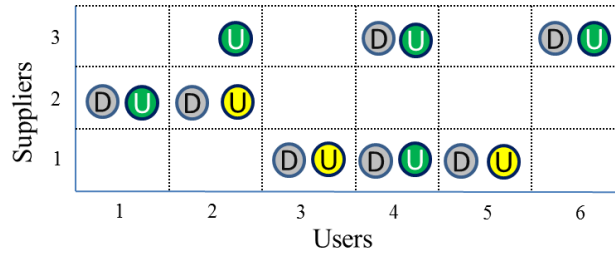


Figure 5.10 Comparing effects of the supply uncertainty on optimized flow exchanges in the multi-objective model

The results show that under the supply uncertainty, user 2 needs to shift its supplier from 2 to 3. Suppliers can partially support the demand of user 3. The supply of user 5 is weakened as well. Under the supply uncertainty, user 6 is always supplied completely.

Uncertainty in supply prices: In a real condition of the supply market, there are several competing sources of supply. Improvements in technology could lead to the cheaper price for a raw material. In the energy market, the evolution of energy generations using renewable sources in small and medium size enterprises could reduce supply prices. In this case, a user prefers to shift its material/energy supply into other sources. It is assumed that the current cost of supplying energy will be reduced to 0.054 [€/kWh] depending on energy sources of users. Effects of the supply uncertainty are evaluated using a deterministic multi-objective model as presented in Figure 5.11.

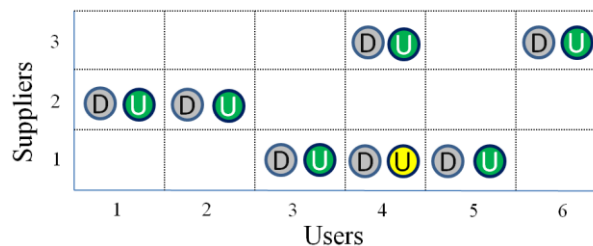


Figure 5.11 Comparing effects of the uncertainty in the supply prices on the optimized flow exchanges in the multi-objective model

Figure 5.11 shows that the uncertainty in supply prices would motivate user 4 to increase its purchase from supplier 3. For user 6, it is preferred to supply more than 50% of the demand from supplier 1 as the result of price uncertainty. Other flow exchanges remain almost the same as the deterministic model.

Tax on carbon: This uncertainty arises from the national or international regulation to limit produced carbon in industries' processes. A review of trends in carbon tax shows that in a short term, countries plan to increase the carbon tax (Maes et al., 2011; Pérez-Valdés et al., 2012). However, in the long term, another scenario could be regulated. It is assumed that the tax on carbon can increase up to 2.5 times of its current rate. For this uncertain parameter, we directly applied increased rates in the model to evaluate the effects. The effects of increases in the tax on carbon on the multi-objective model show no change in the optimized network. The amount of the demand satisfaction is changed for the optimal cost.

Besides the network structure, other indexes are analyzed to investigate the effects of uncertain parameters. The indexes are for the cost and environmental impacts of the synergic networks as summarized in Table 5.9.

In Table 5.9, the percentage of changes in each index compared to the deterministic multi-objective model is measured. This is useful to evaluate effects of uncertainty parameters on the model.

Table 5.9 Evaluations of indexes under the demand uncertainty

Index	Uncertain Parameters			
	Demand	Supply	Price	Carbon Tax
Total Cost of Suppliers	46211861	33970565	43437051	45435418
Change (%)	+4%	-24%	-3%	2%
Total Cost of users (Minus tax)	24931145	26913628	3900179	2201293
Change (%)	+850%	+917%	+33%	-25%
Total Cost (with tax income)	58361994	51775569	35221503	24864281
Change (%)	+66%	+47%	+0.003%	-30%
Total Cost (Minus tax)	71143006	60884192	47337270	47636711
Change (%)	+50%	+28%	-0.002%	+0.004%
Total Pollution	120539557	96640362	91628522	91146732
Change (%)	+32%	+5%	+0.003%	-0.002%

The initial demand uncertainty seems to have the worst effect on indexes. But the most effect is for the increase of flow exchanges, not the uncertainty. Thus, the supply uncertainty affects the network more comprehensively than other uncertain parameters. In addition, Figure 5.11 demonstrates that the uncertainty in the supply uncertainty has provided three uncertain connections in the network. A surprising result in Table 5.9 is the limited effect of the increase in the carbon tax on reducing pollutions.

In order to verify the solution of the stochastic optimization method, a robust optimization model is developed. The aim is to compare solutions obtained from both methods and discuss the compliance and conformity of results. Thus, robust counterparts of the deterministic models are developed and modeled in the AIMMS optimization software package.

Because of complexities in generating the robust counterpart of the proposed model, several levels of uncertainty studies have been conducted. The studies include reviewing effects of individual uncertain parameters, pairs of the uncertain parameters, and all uncertain parameters. To compare the results, outputs of robust models for individual uncertain parameters are compared in Figure 5.12.

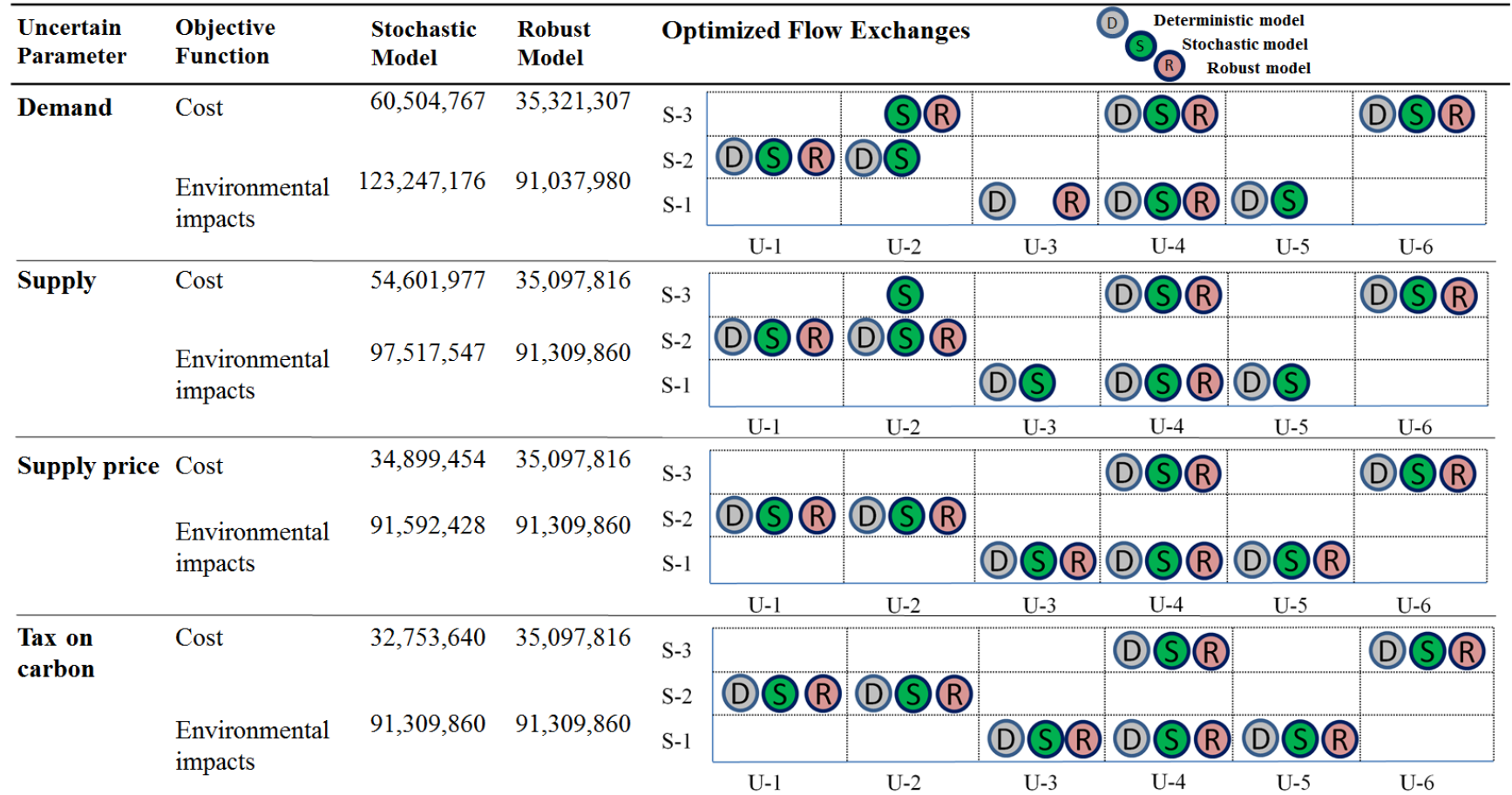


Figure 5.12 Comparing the optimized flow exchanges using the stochastic and the robust models

In Figure 5.12, the optimized flow exchanges are mostly compatible specifically for Supply price uncertainty and Tax on carbon uncertainty. A minor change in the optimized network configuration is witnessed to supply the second and third users (U-2 and U-3) under demand and supply uncertainties. The difference could be justified for the value of demand and the logic of stochastic optimization. As discussed in the presented solution approach, it is assumed that all scenarios ($N=10$) have the same occurrence probability. A different probability for the scenarios could end to different flow exchanges. However, the robust model has provided less cost for the optimal configuration; therefore, the result of the robust model can be selected for implementation.

In summary, it is believed that some connections are resilient to be affected by uncertainties. The flow exchanges between supplier 2 and user 1 (S2-U1), (S2-U2), (S3-U4), (S1-U5), and (S3-U6) exemplify such resilience in the reviewed industrial case. Thus, the EIP managers could trust such flow exchanges for the optimized symbioses network.

The research conducted in this Chapter has been published in the following conference proceedings:

- Afshari H, Peng Q, and Farel R. Improving the Resilience of Energy Flow Exchanges in Eco-Industrial Parks: Optimization under Uncertainty. Accepted paper in the ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering. December 2016.
- Afshari H, Peng Q. Need for Optimization under Uncertainty: Designing Flow Exchanges in Eco-Industrial Parks. In the proceedings of ASME International Design

Engineering Technical Conferences & Computers and Information in Engineering Conference IDETC/CIE 2016, Charlotte, NC, USA.

- Afshari H, Farel R, Gurlia J-P, Peng Q. Energy symbioses in Eco-Industrial Parks: Models and Perspectives. In the proceedings of ASME International Design Engineering Technical Conferences & Computers and Information in Engineering Conference IDETC/CIE 2016, Charlotte, NC, USA.

The results are also submitted, or planned to be submitted as following:

- Afshari H, Peng Q, and Farel R. Optimizing flow exchanges in eco-industrial parks (EIPs) using industrial symbioses: concepts and models. Submitted to the International Journal of Cleaner Production.
- Afshari H, Peng Q, and Farel R. Extension of industrial symbioses to residential complexes: models, opportunities and challenges. To be submitted in the Journal of Resource, Conservation and Recycling.

Chapter 6

Conclusions and Recommendations

The sustainable solution for product and system design should include all sustainability pillars including the economy, society, and natural environment. However, uncertainty as the lack of data/knowledge or trust in knowledge affects the sustainable solution. This research proposes a framework to include uncertainties of sustainability pillars in the design phase of a product. The method is extended to design a sustainable system under uncertainty. The research has been conducted in three stages: (1) to quantify uncertainties in social and technological aspects of a sustainable product using two innovative methods (agent-based model and Big Data); (2) to assess effects of the quantified uncertainty on sustainable product design, and minimize the cost and environmental impacts of a product design process using control engineering and mathematical programming; (3) to develop a model for the

sustainable system design under multiple uncertainties using the multi-objective optimization.

6.1 Concluding remarks and research contributions

This research bridges the gap in the literature for methods to practically apply uncertainty studies in the product design process and sustainable systems. The existing deterministic approaches for product design fail to provide the optimal solution in a dynamic environment. By including uncertainty quantification and evaluation, a designer can efficiently address changes required in a product design to minimize its cost and environmental impacts. A list of research accomplishments and major findings of the research are summarized as follows:

- In a knowledge economy, a significant part of a company's value may consist of intangible assets. It is believed that the knowledge economy depends on more intellectual capacities than physical inputs as a key aspect (Powell and Snellman, 2004). For an efficient use of intellectual properties in the product development process, this research developed cost-effective methods to estimate changes in product components using agent-based modeling and Big Data during the product life cycle. The early knowledge of the product changes will minimize the cost and increase the efficiency of design decisions.
- In Chapter 3, the proposed agent-based method focuses on the ability of agents in the multiple domain analysis of changes. Technical and social interactions are defined for a set of autonomous agents. Agents' behavior for a specific duration (the product life cycle)

is simulated. The proposed agent-based method can help formulating the mathematical representation of interactions.

- A competence method based on Big Data analytics is developed to overcome shortcomings of the proposed agent-based model in terms of technical factors, social factors, and scope of study. The method quantifies the changes in customers' preferences using social network mining. After quantifying the external uncertainty, effects of the dependencies between components of a product are evaluated. The changes are then transferred into components to determine the most affected components during the product life cycle.
- Results of the proposed method for the smartphone are discussed in detail. Real changes of the smartphone during its life cycle are used to assess the accuracy and efficiency of the proposed methods. Some error indexes are used to quantify the error measurement. Moreover, a change propagation method (GVI) applied for the smartphone (Nadadur et al., 2012) is used to compare the results. Both of the proposed methods have shown interesting results; however, the method based on Big Data analytics has shown a better convergence to real changes of the smartphone. It is noticed that evaluating dependencies between components of the smartphone could increase the accuracy of the methods.
- In Chapter 4, a comprehensive approach to reduce effects of the uncertainty on environmental impacts of the design process is presented. The method considers changes of customers' preferences using an indicator of the generational variety uncertainty in a product life cycle. The research emphasizes the design solution for minimizing environmental impacts of products. The research deliverable is the highlighted product design parameters (DPs) that affect environments with quantified measures of

environmental impacts loads. Moreover, effective DPs are decided under constraints in design activities related to the budget limitation.

- In Chapter 4, a method to evaluate effects of unexpected disturbances on coupled design tasks is proposed as well. Two models are developed to optimize design iterations under disturbances. The proposed method is based on a non-homogenous state-space representation to minimize the design iteration. Two mathematical models are developed to minimize the cost and environmental impacts of the design process. The methods are applied to a smartphone design process. For the iPhone example, it is proved that changes of users' preferences have increased the cost and environmental impacts of the design process. Proposed models can find the optimum number of design iterations under changes of users' preferences. The proposed method is essential for products with a long life, as multiple generations of the product may be introduced to the market during the product life cycle.
- One of the major contributions in this research is including all sustainability pillars in the proposed approach. The research addresses the users' preferences to highlight the role of individuals in the society. Moreover, the economic and environmental objective functions have been considered for optimal decision making in the design process.
- In Chapter 5, the framework for sustainable design under uncertainty is extended to sustainable systems. While creating synergies and symbiosis has all economic and environmental advantages, finding the optimum way for the redistribution of energy produced in some processes requires other technical matches (e.g., thermodynamic compatibility for heat flow). In this case, cost saving is not trivial. In this chapter, industrial symbiosis networks with the emphasis on energy networks are discussed. By

addressing important decisions in energy symbioses networks, two models to optimize energy symbioses networks are presented regarding stakeholders' perspectives. The models search for optimal synergies between individual industries in an EIP. Both models minimize the annual cost of networks considering maximized synergies between industries.

- Chapter 5 also brings the attention to the importance of considering uncertainties in the optimization problem for the flow exchange optimization in designing EIPs, and proposes a multi-objective model for the symbioses creation. The model minimizes the total annual cost of synergic exchanges while minimizing the total environmental impacts of flow exchanges between industries. This is important because the sustainability of EIPs and its symbiosis not only relies on economic bases, such as the oil price decreased recently, but also on the environmental motivation such as the CO₂ emission regulated by the government. This chapter reviews briefly uncertainty factors in EIPs, and studies the effect of formulating uncertainty parameters in the optimization problem using a case application of industrial but anonymized data. The deterministic multi-objective model is then compared to models with uncertain parameters to highlight the effect of uncertainties on the industrial symbioses decisions. The contributions are (1) proposing multi-objective models for multiple types of symbioses to address minimizing the environmental impacts directly; (2) formulating technical and economic measures in the flow exchange optimization; (3) integrating uncertain parameters in the optimal structure of energy symbioses networks.

6.2 Research limitations and recommendations for future research

Although this research proposed an innovative approach to include uncertainties in design of the sustainable product and system design, there are still many opportunities to improve in this field. Research limitations in terms of data and resources are lack of the access to accurate sources of data for Big Data analytics and the lower number of experts in qualitative analyses such as the axiomatic design in case studies. In terms of methods, the uncertainty modeling is limited to the basic diffusion theory that is required to be improved. Also, the optimization models in Chapter 4 are the single objective, which does not reflect the accumulation of environmental and economic indexes. A list of possible future research is presented as follows:

- A common challenge in the Big Data analytics project is a lack of access to accurate data. In the proposed Big Data method, the Google trends tool has been trusted in the role of valuable source for the Big Data analytics as confirmed in several other studies. However, a comprehensive analysis using other Big Data sources is expected for future research.
- The basis of the agent-based model is an extended version of the basic diffusion theory shown in Equation 3.1. The aim is to evaluate effects of social interactions and mass media on people's preferences when such changes of preferences matters for a manufacturer. However, one may use other theories to include dynamic variables in the market analysis such as the utility of consumption in economics.
- In Chapter 4, two models were introduced to minimize the cost and environmental impacts of a product during the product development process. The proposed models can be extended to other decisions in the product design process because uncertainty would

influence other decisions as well. For example, the uncertainty can affect decisions in the product supply chain or manufacturing level. Such integrated framework to incorporate uncertainty in different levels is proposed for further research developments.

- The presented models to optimize symbioses networks can be extended for other objectives such as maximizing efficiency indexes. Moreover, values for uncertain parameters could be measured instead of assuming the values. Agent-based modeling can be used for uncertainty studies. As the uncertainty is inevitable in engineering systems, suggesting models to overcome multiple uncertainties will be examined in the future research.
- Harvesting unused/wasted materials or energies in an EIP can benefit users such as residential complexes. The residential complexes can be a perfect match/customer in an industrial symbiosis because of the almost fixed variation in demand and lower range of the heat used in the daily life. Proposing such integrated and sustainable systems can extend the application of industrial symbioses to non-industrial users in the society. As a result, the society would benefit less CO₂ emissions for less new energy generation.
- The reliability and continuous access to the recovered materials/energy remain as a challenge for further applications of industrial symbioses. For energy symbioses networks, a talented way to improve the access rate to the required energy is to combine existing networks with renewable energy generation sites. In this case, the need for burning fossil fuels to compensate unsupplied energy would be satisfied. Therefore, the possibility and feasibility of combining industrial symbioses networks with renewable energy generation networks are proposed for the future research.

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Appendix A

Functional Requirements Customer Requirements	Display	Touchscreen	Sound		Processing & Memory	OS	Apps	Data Download and transfer				Internet & Connectivity	Power Capacit	Connector cable	GPS	Cameras	Casing
	Size Resolution	Size Technology	Audio codec Mic sensitivity Speaker loudness	Speed Capacity				GSM & CDMA Frequencies Baseband processor Baseband memory support	Download transfer speed	WiFi speed Standards Bluetooth					Resolution Video	Housing parts Interactive parts	
Display																	
Large size display	✓															✓	
High-res disp		✓															
Easy touchscreen operation			✓	✓													
Scratch-resistant screen				✓													
Sound																	
Sound-Good quality					✓	✓	✓										
Sound-Support different music file																	
Sound-Fast processing					✓		✓		✓	✓							
Sound-Large storage capacity									✓								
Data transfer/Download																	
Fast								✓	✓	✓	✓	✓		✓			
Easy to sync						✓							✓				
Connectivity																	
Multiple carriers								✓	✓								
Good coverage								✓	✓								
Internet																	
Easy WiFi connectivity											✓						
Easy web browsing											✓						
Easy emailing facility											✓						
Easy video viewing	✓	✓								✓							
OS and applications																	
Cool and versatile OS					✓		✓										
Wide selection of apps						✓	✓										
Easy app download and install					✓		✓							✓			
Easy to customize and update						✓	✓							✓			
Multitasking capability					✓		✓										
Power management																	
Simple charging													✓			✓	
Short charging time																	
Long b/w charge intervals													✓				
Reliable																	
Robust and sturdy																✓	
No software glitches						✓		✓								✓	
Others																	
Easy to activate silent mode																✓	
Customizable ringtone							✓										
Easy typing	✓	✓	✓	✓		✓										✓	
Voice activation					✓	✓										✓	
Global positioning (GPS)			✓	✓	✓	✓				✓	✓			✓		✓	
Good front & back camera															✓	✓	
Overall sexiness (aesthetic)	✓	✓											✓			✓	

Figure A. 1 First QFD matrix for the smartphone

Smartphone components Customer Requirements	Display	Touchscreen	Sound	Processor	DRAM memory	Flash Memory	Data transfer	Internet & connectivity	Software	Battery	GPS	Cameras	Outer facing	Physical Interfaces
Display														
Size	4.18	4.18											4.18	
Resolution	4.71	4.71												
Touchscreen														
Size	3.10	3.10											3.10	
Technology		37.56												
Sound														
Audio codec			1.10											
Mic sensitivity			2.89											
Speaker loudness			2.32											
Processing & memory														
Speed				57.33	6.37									
Capacity						4.32								
OS				26.46	4.41	4.41			13.23					
Apps				13.26	4.42	4.42			13.26					
Data Download and transfer														
GSM & CDMA							12.78							
Frequencies							4.26							
Baseband processor							9.54							
Baseband memory support							3.87							
Download transfer speed							10.53	10.53						
Internet and connectivity														
WiFi speed Standards								8.56						
Bluetooth								3.40						
Power capacity										7.43				
Connector cable														
GPS									8.31		16.62			
Cameras														
Resolution	0.68								2.04			4.08		
Video									7.26			2.42		
Casing														
Housing parts												10.63	63.78	31.89
Interactive parts			1.39									1.39	4.17	4.17
Magnitude of Changes	12.65	49.55	7.70	97.02	15.20	13.15	40.95	22.49	44.10	7.43	16.64	18.49	75.23	36.06

Figure A. 2 Calculation of magnitude of changes for the smartphone