HÖGSKOLAN
DALARNA

Dalarna Doctoral Dissertations

A data-driven decision support system for coherency of experts' judgment in complex classification problems

The case of food security as a UN sustainable development goal

RUEBEN LARYEA

Microdata Analysis
School of Technology and Business Studies
Dalarna University, Sweden
2018

Dissertation presented at Dalarna University to be publicly examined in B311, Borlänge, Wednesday, 28 November 2018 at 12:30 for the Degree of Doctor of Philosophy. The examination will be conducted in English. Faculty examiner: Dr. Jay Liebowitz (Harrisburg University of Science and Technology).

Abstract
Laryea, R. 2018. A data-driven decision support system for coherency of experts' judgment in complex classification problems. The case of food security as a UN sustainable development goal. *Dalarna Doctoral Dissertations* 8. Borlänge: Högskolan Dalarna. ISBN 978-91-85941-79-7.

Everyday humans need to make individual or collective decisions. Often the decisions aim at achieving multiple goals (thus involving multiple criteria) and rely on the decision maker(s)' intuition, internal data, as well as external sources of data. Faced with a complex decision problem of this kind, it is a great challenge to decision-makers to be logically coherent over time with regard to their preferences. To aid in achieving coherency, operation researchers and decision analysts have developed formal methods to support decision makers. One such method is the UTADIS method that serves as the workhorse for this thesis. I received the request from UN officials who had to manage the sustainable development goals while addressing the issue of food security. They wished for a decision support system (DSS) that could aid in their classification of countries to mitigate the risk of failing on food security. The virtue of the DSS should be that their expert judgment was complemented by formal methods for better risk classification. The UTADIS method was fitting for the purpose, but it lacked implementability. In particular, it required an iterative approach engaging the experts multiple times, while not readily lending itself to making use of external data, making it inefficient as a DSS. The fundamental contribution of this thesis is that I have solved these shortcomings of the UTADIS method, such that it now readily can be used in a functionally efficient way for the desired purpose of the UN. In solving these problems, it is also more broadly implementable as a DSS, as I have validated the artifact to a DSS, by use of several demonstrations and exposed it to sensitivity analysis.

Keywords: Coherence, Efficiency, Decision Support System, Multi-Criteria, Risk, Classification Model, Decision Makers, Judgment, Alternatives, Prediction, Data, Integrate, Imprecision, Food Security, UTADIS

Rueben Laryea, School of Technology and Business Studies, Microdata Analysis,

© Rueben Laryea 2018

ISBN 978-91-85941-79-7
urn:nbn:se:du-28649 (http://urn.kb.se/resolve?urn=urn:nbn:se:du-28649)

Dedicated to the memory of the former Secretary General of the United Nations, Mr. Kofi Annan, whose tenure of office initiated the sustainable development goals.

Acknowledgements

I am thankful to God for providing me with very helpful supervisors in the name of Professor Kenneth Carling, Catia Cialani, Roger Nyberg and Ioanna Farsari. My deepest gratitude goes especially to Professor Carling for his personal drive and patience in ensuring that this PhD thesis in Microdata analysis at Dalarna University has become a reality. I have learnt a lot from the hard-working nature of Kenneth and his progressive enthusiasm in getting things done. I now feel equipped with the mental strength, knowledge, patience and the right attitude to face the future because of the guidance of my supervisors. I am thankful to my supervisors for molding me to this successful stage in my life. I also wish to express my gratitude to my examiner Professor Mark Dougherty, who facilitated the transfer of my courses to Dalarna University, not forgetting to mention Märet Brunnstedt for her help in making everything possible administratively. I am also thankfull to Professor Emeritus Irene Gilsenan Nordin for making available her proofreading expertise in helping me present my thesis in a final good shape.

I am grateful to my parents, Mr. Bennet Quaye Laryea and Mrs. Patience Laryea, my sisters, Dr. Lily Laryea and Miss Joycelyn Laryea for their support and prayers in the years that I had to spend on this PhD mission. I will never forget the emotional support and strength my parents and sisters provided me with when the journey was tough and I needed some strength to carry on. They have always been there for me and been very understanding and supportive. God bless you abundantly.

Professor Karl.W.Sandberg, you have been my personal advisor and friend from the days of my Master's degree untill now, and you have always come to my rescue in difficult times. Your valuable advise helped me in my career, both in industry and academia. I greatly appreciate your advise and willingness to take the initiative in salvaging me from situations beyond my understanding. I value your passion in your work and your readiness to come to my rescue whenever I called on you over the years. I am truly grateful.

To the team at the United Nations in Manhattan, New York, particularly, Rene Clausen Nielsen, Tomaz Logar and Alex Rutherford who helped me with the data and resource persons to formulate the problem and scope of this research, I say a very big thank you.

I am also thankful to my PhD colleagues at Dalarna University, namely, Ilias Thomas, Ross May, Murshid Saqlain, Asif Huq, Yujiao Li, and Vijay Pratap Paidi who have been very cooperative and helpful with their advise and in providing directions to help make me feel comfortable with my PhD studies at Dalarna University. Many thanks also go to staff members of Dalarna University whom I have had the privilege of interacting with, namely, Dr. Mengjie Han, Dr. Xiaoyun Zhao, Professor Moudud Alam, Professor Lars Rönnegård and Ola Nääs.

To all other staff members of Dalarna University whose names I may not have mentioned here, I really appreciate your kind cooperation in helping me finish my PhD studies at Dalarna University. I thank you all.

List of papers

This thesis is based on the following papers, which are referred to in the text by their Roman numerals.

I Laryea, R. (2013) ‘Project outcome classification with imprecise criteria information’, Int. J. Applied Decision Sciences, Vol. 6, No. 4, pp.372–387

II Laryea, R. (2013) ‘A multi-criteria prediction model for project risk classifications’, Int. J.Decision Sciences, Risk and Management, Vol. 5, No. 1, pp.55–79.

III Laryea, R., Carling, K. and Cialani, C. ‘A Food price volatility model for country risk classification’, Int. J. Risk Assessment and Management.(submitted)

IV Laryea, R., Carling, K.,Cialani, C. and Nyberg, R.G. (2018) ‘Sensitivity analysis of a risk classification model for food price volatility’, Int. J. Risk Assessment and Management, Vol. 21, No. 4, pp.374–382.

V Laryea, R., Farsari, I. and Nyberg, R.G. ‘A decision tool approach to sensitivity analysis in a risk classification model’, Int. J. Risk Assessment and Management.(submitted)

Reprints were made with permission from the publishers.

Contents

Glossary

Accuracy – Total number of correct predictions as compared to the total number of cases.

UTADIS – UTilities Additives DISkriminantes.

Criteria – Variables that go into decision making.

Alternatives – Options available for decision makers.

Risk – Probability of an uncertain danger caused by internal or external vulnerabilities.

Satisfactory decision – Decision that includes the preferences and uncertainties decision makers have to deal with.

Judgment – the role of intuition in decision making.

Classification – the assignment of a finite set of alternatives into predefined groups.

Mitigate – to strategise against the severity of an event.

1. Introduction

A vehicle driver wakes up in the morning and plies a certain route everyday. With years of experience, the driver is very conversant with the road network and is thus aware of all the events which occur on this route whilst driving. This same driver, who is very much used to the conditions on this road, had the opportunity for the first time to drive a heavy goods vehicle to cart heavy goods to a customer, using this same route. On a curve on this same route, the driver, now handling a heavy goods vehicle miscalculates the bend and how it should be maneuvered with a heavy goods vehicle and thus runs into a ditch. The driver reverses out of this ditch and tries to maneuver the bend again but drives into this ditch again, this time bursting his vehicle tire and overturning some of the carried goods onto the road in the process, causing inconvenience for himself and fellow road users. After several maneuvers, the driver gets used to the situation and is able to take the bend and proceed on his route. It is obvious that despite several years of experience in driving, the driver encountered a new situation which he is not conversant with, and thus could not predict or strategise to take care of this situation. It, thus, costs the driver time and inconvenience by trying out several maneuvers before he can overcome the situation. One may ask, would it not have been more efficient and convenient for the driver if he had sought expert advice on how to handle this new situation and save himself the time and inconvenience in this new situation? It is obvious here that if the driver had some new information to help him understand this particular situation of handling a heavy goods vehicle in a bend, this would help him in judging the risk and predicting the possibilities of managing this bend. Then, combined with his driving experience, the driver could have handled the situation in a more efficient manner. The driver believed that his years of driving experience could take care of this new situation, forgetting that this is a new situation which requires new information to help him judge, classify and predict the risks associated with maneuvering such a bend with a heavy goods vehicle. But it is understandable that even though the driver had been in the driving business for a long time, he is not well-equipped in this new driving situation to get it right with the first execution of the bend, because he has not experienced this situation before and has judged wrongly, thus making wrong and inefficient decisions.

Day in and day out, decision makers are faced with new risky decision-making problems like this driver finds himself in, and if not well-versed in how to strategise, classify and prioritize the decision-making process, the associated risks would have dire consequences for their businesses and partners as well.

Risk and decision analysts and operation researchers work to arrive at best practices for any individual or group of decision makers, who would want to examine the possibilities of identifying risky events and their consequences in decision-making processes. This would enable decision makers to prioritize the risks associated with the alternatives to establish a least-to-most critical importance ranking of the alternatives. Critically ranking alternatives into risk groups provides insights for the decision makers as to resource allocation to manage or mitigate the occurrence of high risk activities in the decision-making process. Risk assessment is vital in creating awareness of project exposures and negotiating with investors, thus working according to a credible project plan to fund the project. It has therefore become imperative to build reliable risk assessment models to assist decision makers in classifying their projects into classes of risk in the course of managing their projects.

Project risk assessment models can be used in differentiating between failed projects and non-failed projects. Traditional optimisation, statistical and econometric approaches often used in risk prediction models, for example, the revenue maximizing model [1], the managers, utility model [46] and the satisfying model [25], are often based on the assumption that the considered problem is well-formulated and they usually consider the existence of a single objective or evaluation criterion [45]. In such a case, the solution to the problem is not far-fetched. However, in reality, the forming of such project risk prediction models is based on a different kind of logic, taking into consideration the existence of multiple criteria, the conflicting situation between the criteria, the complex, subjective and ill-structured nature of the evaluation process and the integration of the decision makers in the evaluation process [7].

Operation researchers have therefore adopted this innovative, comprehensive and realistic perspective, which overcomes the restrictive framework of traditional optimization and statistical analysis [35]. An example of this is for financial decision problems, such as the choice of investment projects, portfolio selection and the evaluation of business failure risk. Due to the complexity of such decision problems, it becomes an illusion to speak about optimality since multiple criteria must be taken into consideration [12]. It is termed an illusion because in the Multi-Criteria context, a set of alternatives are considered, and decision makers seek to make ”optimal” decisions considering all the criteria that are relevant to the analysis. Since these criteria often lead to conflicting results and conclusions, the ”optimal” decision is really not optimal in the traditional optimization sense. Instead, it is a satisfactory, non-dominated decision, that is, a decision that is in accordance with the decision maker’s system of values and not dominated by other possible decisions [12]. Thus, due to the multi-dimensional character of such decisions, decision makers seek Multi-Criteria Decision Analysis (MCDA) methodologies and system tools to support their decision-making processes. The advantages that the MCDA paradigm provides in decision making include the possibility of structuring complex evaluation problems, the introduction of both quantitative and qualitative criteria in the evaluation process, transparency in the evaluation, allowing good argumentation in decisions and the introduction of sophisticated, flexible and realistic scientific methods in the decision-making process. Most important of all, MCDA enables the decision maker to participate actively in the decision-making process, and supports him in understanding the peculiarities and the special features of the real-world problem that he faces [48]. Thus, the decision maker is not only restricted to implementing an ”optimal” solution from a mathematical model, but participating in the model-formulation process as well as in the analysis and implementation of the results, according to his judgment.

1.0.1 Research Contribution and Motivation

When judgmental decision making is assessed against coherence criteria, humans often appear incompetent and irrational [27]. Many decisions people are faced with, whether individual or collective, involve inferences or intuition, and assessments of such inferences, intuition, or reasoning processes of decision makers spread apart bidirectionally [29], because decision tasks involve inferences which tend to be ambiguous, contradictory and complex [34]. A group of decision makers, who would want to examine risky events and classify alternatives based on risk, thus have problems being coherent in their judgments of their choices, because of the unstructured nature of data, and conflicting multiple criteria [7]. Real-life decision problems take into consideration complex, subjective and unformulated evaluation processes, and decision makers are required to be coherent in solving such problems [27]. Aiding decision makers in being coherent with methods that integrate multiple criteria, will provide decision makers with information on trends and patterns in data, to enable decision makers to prioritize the risk associated with alternatives and be able to allocate resources efficiently.

For this research, I was approached by decision makers at the United Nations (UN) concerning the sustainable development goal of food security [13], in which the decision makers want to mitigate Food security risk. Food security in the context of this research refers to economic access to nutritious and affordable food. Therefore, the decision makers want to mitigate the risk that escalating food prices would prevent people from having access to nutritious food globally. The UN have food price criteria for the projects which overlap and do not integrate for strategic decision making. The situation therefore calls for criteria aggregation models which would reveal the risk level of criteria, and integrate the different criteria and the risk levels in decision-making processes, so that the projects and countries can be well-separated into risk classes of the sustainable development goals. Moreover, the decision makers should be able to generate suitable risk models which would aid the UN in predicting the countries or projects into their preferred risk classes, in the long run, as the projects progress and require monitoring. The decision makers will need to be coherent in their inferences when it comes to uncertainties in the price data, and be able to integrate the conflicting multiple criteria on food prices to form a basis for decision making. Here, we have a coherency problem in efficient decision making, because decision makers would have to deal with the complexities of intuition and inferences from multiple criteria on food staple prices which are not integrated, thus making decision making for decision makers bidirectional and incoherent.

Failure by decision makers to be coherent in efficient decision making on this project would lead to the wrongful allocation of resources and its dire consequences for the sustainable development goals. The decision makers have preferences which have to be considered in the solution to this problem. Risk classes of Alert and Crisis are defined by the decision makers as their preferred risk classes, in which they want to classify the countries, alternatives, which the decision makers have identified as the trouble spots. The UN are interested not only in classifying the projects on risk levels, but want to have clear information on what the actual risks of the individual projects are. This calls for a risk-classification decision support system that would be able to complement the judgments of the decision makers with formal methods for a better risk classification. I therefore identified data-driven classification [31] as the solution in providing a decision support system for this problem, because of the requirements the UN had provided on the data of food prices criteria and country relationship, combined with the preferred risk classes of the decision makers. Then, I had to identify a suitable classification algorithm and framework which would serve as the decision support system, and would have the capacity to consider and integrate the present and future uncertainties in price data, and reveal the risk levels on food prices to the decision makers. Moreover, the decision support system I identify had to consider the preferences of the decision makers in being coherent for efficient decision making, and further develop a data-driven predictive classification model which would be satisfactory to decision makers in predicting future data sets.

I therefore identified a preference disaggregation Multi-Criteria Decision Analysis (MCDA) method, the UTilities Additives DISkriminantes (UTADIS) [12], as the right method, compared to all other methods, for meeting the requirements as set out by the decision makers on this project. The MCDA methodology that is used for the prediction of project failure originates from the preference disaggregation approach [17]. The preference disaggregation approach refers to the analysis of the global preferences of the decision maker, in order to identify the criteria aggregation model that underlies the preference result. Preference disaggregation analysis uses common utility decomposition forms to model the decision makers' preferences and uses regression-based techniques. With preference disaggregation analysis, the parameters of the utility decomposition model are estimated through the analysis of the decision makers' overall preference on some reference alternatives. The problem is then to estimate a utility function (usually additive) that is as consistent as possible with the known subjective preferences of the decision maker [48]. The discussions as to the choice of the UTADIS method, compared to all the other methods, and operation of the UTADIS are detailed in Chapters 3 and 5, respectively. Suffice to note here that, the UTADIS method is selected because it provides room for the incorporation of the preferred risk classes of the decision makers, it provides a predefined classification, whereby, the decision makers are engaged in modeling the data into the risk classes and it does not have to demand so much guess work from the decision makers, compared to other methods, in arriving at an accurate predictive classification model. The UTADIS and the ELECTRE TRI have been proven to be the most effective methods [39] for this area of Multi-Criteria Classification decision making, and I have argued further why I narrowed down on the UTADIS method for this work in Chapter 3.

However, I had to modify the UTADIS classification framework to make it more efficient in its operation as a decision support system for this research, so as to help the decision makers in being coherent in their judgments in arriving at a validated and accurate classification predictive model. The original operation of the UTADIS classification framework, as proposed by Zouponidis & Doumpos (2002) [12] (Chp.1 p.18), involves a time-consuming iterative process and is problematic for coherency of multiple decision makers, when it comes to the data at hand for this research. The data involved uncertain time interval, and is not readily fit for the operation of the UTADIS classification framework, so I had to identify methods which would restructure the data to solve the problem of uncertainty, and reveal trends and patterns to aid the decision makers with more information, enabling them to be logically coherent in their judgments, and arrive efficiently at an accurate predictive classification framework. This, I do by introducing data modeling techniques in the predefined classification of the UTADIS to aid the decision makers in being logically coherent in modeling the data on the alternatives into their preferred risk classes, and validate a predictive classification model to be accurate in an efficient manner. I execute the classification framework just once to arrive at a validated and accurate predictive classification model, compared to the iterative and time-consuming process originally proposed by Zouponidis &Doumpos (2002) [12] (Chp.1 p.18), which can be costly for managerial decision making. The objective of the data modeling technique introduced in the predefined classification is to reveal trends and patterns of information which are otherwise hidden in raw data, thus aiding decision makers in being coherent with the data modeling process to classify decision alternatives into the preferred risk classes of the decision makers. I realized in this research that by supplementing the work of the UTADIS method with the data modeling method in the predefined classification, the decision makers are aided in becoming logically coherent, and the classification methodological framework is executed just once for the predefined classification to match the UTADIS method's classification, thus arriving at a validated and accurate classification predictive model in an efficient way.

I further conduct a sensitivity analysis to generate relative values of the weights in the accurate classification predictive model and the country alternatives in a paired comparison, together with fixed-point and judgment analysis from a scale, to produce a mixed model, which is used to rank countries at high risk food price volatility. Since in real-life situations, the weights of the criteria may vary with time, due to possibilities of data alteration for decision making, I also use an automated tool DecideIT [9] to vary the weights of the accurate classification model. I then conduct a ranking of the country alternatives and determine the most sensitive criteria capable of altering the position of a country.

Figure 1.1 below presents a general overview of the papers that I used in solving the research problem. The solutions in Papers I, II and III provide avenues for decision makers to take to be logically coherent, complemented with formal methods to efficiently develop an accurate predictive classification model satisfactory to decision makers.

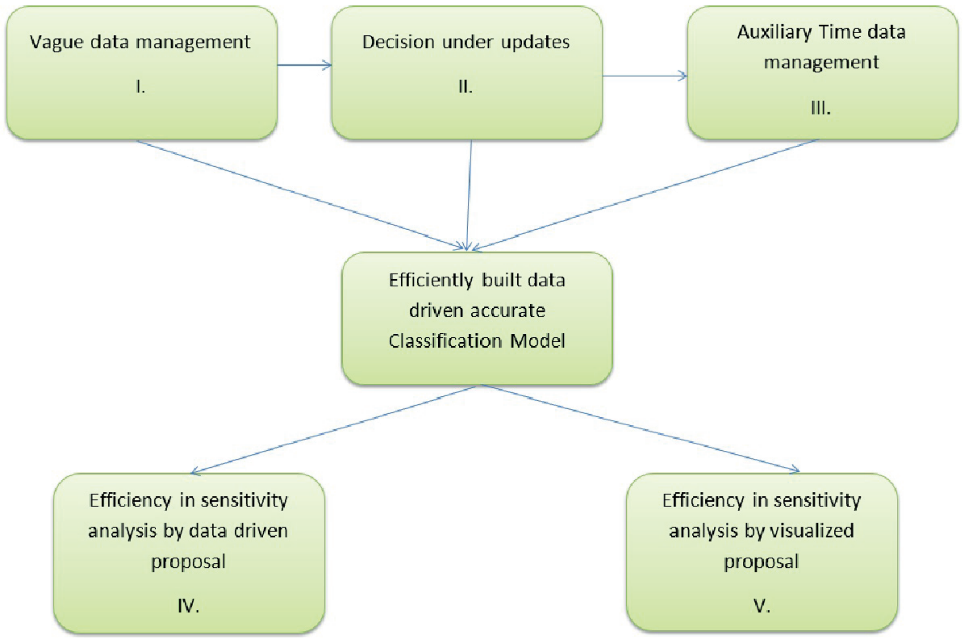

Figure 1.1. Schematic overview of the thesis graphically

The solutions in Papers IV and V carry out a sensitivity analysis of the predictive classification model and allow decision makers the flexibility of including imprecision, guided by the risk levels of the criteria in the predictive classification model. This enables a ranking of the alternatives, so as to be able to prioritize the most high risk alternatives, and further determine which criteria to focus on, in mitigating the risk of food security, being the case considered here.

1.0.2 Research Methodology – The Design Science Paradigm

Scientific paths in pursuing the creation of an artifact are defined by design science. Practical problems are solved with artifacts to reveal interesting information for people to understand in all fields of work. Design science triggers problem investigation, interaction between effects, artifact and context of problem investigation for treatment design, and design validation for effects to satisfy criteria and analyze changes in artifact and context. Treatment implementation requires the artifact to be demonstrated and put into practice, and finally evaluated. Design Science is perceived as knowledge containing, with knowledge ranging from design logic, construction methods and tools to assumptions about the context in which the artifact is intended to function [14].

Design science is solution-oriented and can be handled by more than one scientific method considering improvements to a defined step and goal to be attained [19]. The artifact as an object is made by humans with the purpose of addressing a practical problem [4]. The evaluation of a designed artifact highlights its ability in the solution of a practical problem, in accordance with the stated requirement in the artifact [3]. The artifacts in Design Science can broadly include models, methods, constructs, instantiations and design theories [22][14], new explanatory theories, new design and developments models and implementation processes or methods [16]. Design Science thus focuses on the development and performance of a designed artifact with the explicit intention of improving the functional performance of the artifact. The artifact enables the researcher to obtain a better grasp of the problem and can be expressed in explicit or embedded forms.

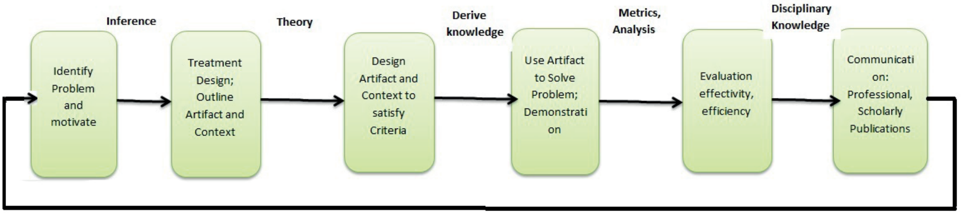

Figure 1.2. The design science Method

Figure 1.2 shows the detailed description of the design science process for conducting an inquiry process. It consists of five main steps, with the sixth step requiring communicating the knowledge and solutions for scholarly or professional publications. The processes start with *Identifying and motivating a problem definition* to show the importance of the problem. *Defining requirements* with the objectives of outlining an artifact, for a solution on what a better artifact can accomplish, involves theories for the *design and development* of the artifact. The artifact is then used in a *demonstration* to find a suitable context for solving a problem, by applying metrics and analytical methods to derive knowledge. The artifact is further *evaluated to show how effective or efficient* it is for solving the problem definition from the beginning. The disciplinary knowledge is then *communicated through scholarly and professional publications*.

This dissertation consists of contributions which follow this structure of activities, as shown in the design science process. By applying the methodological structure of design science, the research identified methods which satisfy each stage of the design science process for the artifact to solve our problem definition. The artifact in this dissertation is a decision support system for classification problems and consists of two parts. The first part is modified in order to aid decision makers in being coherent in their judgments, and model data in a predefined classification process, so as to produce an accurate classification model efficiently. The second part of the artifact consists of a Multi-Criteria Decision Analysis (MCDA) classification algorithm - UTilités Additives DIScriminantes(UTADIS) [17]. The UTADIS model is purposely identified as being the best fit for the cases in this dissertation, because it only requires the predefined classification from the first part of our artifact. The method then builds its own weights for criteria, utility thresholds and global scores for alternatives, by simulating the data of the predefined classification to conduct its own classification and produce a predictive additive utility function. This is unlike other existing methods in this domain [24][23][26], which requires as inputs fuzzy information regarding the weights, existing trade-offs and veto thresholds – i.e. very subjective thresholds established to be unconvincing [30]. Given a predefined classification of the alternatives into risk classes, the objective of the UTADIS method is to estimate an additive utility function, and the utility thresholds that classify the alternatives in their original classes with the minimum misclassification error [17].

The research *defines a problem* and relates the solution to a system which supports the human judgment of decision makers in making decisions regarding data modeling, enabling decision makers to classify alternatives into the preferred risk classes of the decision maker of Alert and Crisis. The details of the publications in this study are outlined in preceding sections. The literature review regarding other research and contributions to classification problems which support data-driven decision making is carried out using peer-reviewed contributions selected from existing documented research work, from testing research hypothesis to testing the validity of claims and results. This point of view constitutes the establishment of the bases of future solutions, which enhances the popular research notion that a decision support system should embrace both human and machine processes in an interrelated manner, considering the need for efficiency in accurate decision making.

The artifact used consists of mathematical methods, algorithms that simulate data with software techniques, and an approach that targets improvised ways of decision making, thus driving current states of data-driven classification decision making towards an efficient decision system. The aim of this was to effectively support human judgment in being coherent with machine data modeling thus arriving at accurate risk prediction models. The *outlined requirements* for each contribution are specified as a result of the examination of the existing state of research and current related works in classification. The contributions with their requirements are detailed and discussed in Chapter 3, providing a general overview of all the requirements related to each area in the research executed. The requirements are discussed and presented in further chapters to build the final artifact developed for this dissertation.

The *design and development of the artifact* comprises a classification testing framework and is modified by identifying methods to aid human judgment in a data modeling process for a predefined classification section of the artifact. The other section of the artifact comprises a classification simulation method which simulates data from the predefined classification process to produce an original classification, and a resultant risk classification prediction model, in the form of an additive utility model or marginal utility function. The whole artifact thus consists of two parts: the human judgment induced predefined classification part, and the methodological decision classification part. Modifications and contributions are applied to the predefined classification part of the artifact, depending on the case of study of the decision maker's risk classification preferences, and the whole artifact is simulated to produce a risk prediction classification model of which the artifact is able to evaluate and validate as an accurate risk prediction classification model, with our research contribution producing the risk model in an efficient manner. Thus, the set of contributions forms the modifications to the predefined classification process of the artifact, producing the risk prediction model in an efficient manner and demonstrated in each publication as pieces which develop the artifact together.

The *artifact is demonstrated* such that the future use of the resulting risk classification prediction model to predict accurately for real life situations is validated by the design of the artifact. The experiments carried out with the artifact and the research contribution provide avenues for testing the validity of the artifact and the resulting risk predicting classification model for future use. The capabilities of the artifact are tested by evaluating data inputs in parts of the artifact for problem approaches which apply the artifact to real-life situations, thus producing results validated by the artifact to predict real-life problems into preferred risk classes of the decision maker. The architecture of the artifact comprises two parts which work together to produce a risk classification prediction model which satisfies the preferences of the decision maker. The first part of the artifact consists of a predefined classification process, where decision makers classify alternatives into their preferred risk classes. The second part of the artifact consists of a Multi-Criteria Decision Analysis method,UTADIS. This dissertation modifies the predefined classification process in the first part of the artifact by introducing data modeling techniques to aid the decision makers in carrying out this predefined classification process, thus aiding the behavior and judgment of decision makers in being coherent towards selecting a risk class for their alternative choices. The modification process is aimed at introducing efficiency into the demonstration of the artifact through an effective data modeling process. The data consists of relationships between alternative choices and criteria determined by the decision makers in the decision-making problem, thus, different, imprecise data sources, depending on the decision problem, are used in the dissertation. The data modeled from the predefined classification process is then fed into the second part of the artifact. The UTADIS algorithm, in the second part of the artifact, simulates the data from the predefined classification, calculating global scores of the alternatives and utility thresholds to conduct its own classification, producing a risk classification prediction model in the form of an additive utility function, or a marginal utility function. It is the design of the artifact that: if the predefined classification matches the classification of the UTADIS method, then the resulting risk classification prediction model or the additive utility function are accurate for the decision maker, and thus can be exploited to predict similar future situations into the preferred risk classes. However, if it ends up that the UTADIS method's classification does not match with the predefined classification, then the resulting risk classification model is not accurate. It would therefore not be a suitable classification model to be used in predicting similar situations with future data. Such a case would, thus, require decision makers to re-adjust the predefined classification and carry out the UTADIS simulation again until the misclassification error is tolerable. The work and demonstration of the artifact in this dissertation are thus structured such that the operations of the artifact are modified to help the decision makers in using the artifact in an efficient and effective way.

Evaluating the artifact is carried out to determine if the artifact is able to solve the research problem by tackling the objectives to arrive at the aim of the research. Numerical methods to aid human judgment and computation techniques propel the evaluation process to fuse the results of the two parts of the artifact, thus achieving the aim of the dissertation. The data modeling which aids the predefined classification of the artifact is evaluated using object oriented languages, such as R-programming in R-studio, and c++ for linear programming in MATLAB. The UTADIS method which forms the second part of the artifact is evaluated using a combination of c++ in MATLAB, and Java programming on a web interface to extract the results from MATLAB in the form of Java objects. The results of the dissertation are thus an evaluation of a two-part artifact consisting of a predefined classification, and the UTADIS classification, with the aim of producing an accurate risk classification prediction model sensitive enough to the preferences of the decision maker and produced with an efficient process.

The remaining chapters in the dissertation are organized according to the structure of design science as shown in Figure 1.2.

2. Problem Identification

Investors who examine the possibility of funding a project, or knitting up the activities in a project to arrive at a decision on how viable the project is, would be interested in the project's performance and its means in predicting any possible problems that the project may face. In the course of managing a project, project distress may lead to the failure of a project [11][2][32]. Operations researchers have explored this issue from different points of view, considering the different forms of project distress, including how project failure has a negative effect on organizations and project managers, as investors might lose trust in funding future projects. Particularly, developing economies are often quite vulnerable to project distress and failures, especially when the project occupies a sensitive sector of the country's economy. Also considering the globalization of the world economy, it is obvious that such project failures might be connected to other projects in other parts of the globe and thus have replicating consequences. It has therefore become imperative to build reliable project failure prediction models to assist decision makers, project managers, investors and stakeholders in classifying their projects into classes of risk in the course of managing their projects. Classifying projects into different categories involves uncertainties, because in operations research, assessments and forecasts often arrive from several different units of an organization as separate entities that are not integrated, thus becoming a big task for managers in even building a basis for decision making. There is therefore a need to derive methods for efficient classifications that would incorporate present and future uncertainties in all economic variables, so as to build an appropriate platform for corporate decision making.

I therefore identified a preference disaggregation Multi-Criteria Decision Analysis (MCDA) method, the UTilities Additives DISkriminantes (UTADIS) [12], as suitable for the problem definition, but it lacked implementability. The original operation of the UTADIS classification framework, as proposed by Zouponidis & Doumpos (2002) [12] (Chp.1 p.18), involves a time-consuming iterative process and is problematic for coherency of multiple decision makers, when it comes to the data at hand for this research. The data involved uncertain time interval and is not readily fit for the operation of the UTADIS classification framework, so I had to identify methods which would restructure the data to solve the problem of uncertainty and reveal trends and patterns to aid the decision makers with more information to enable them to be logically coherent in their judgments, and arrive at an accurate predictive classification framework efficiently. Thus, I was obliged to modify the UTADIS classification framework to make it more efficient in its operation as a decision support system for this research, so as to help decision makers to be coherent in their judgments in arriving at a validated and accurate classification predictive model.

In the following, it is assumed that the decision makers have preferred risk classes, and the research is motivated by the following research question:

Considering the preferences of decision makers in classifying alternatives into their preferred risk classes, what is the appropriate classification framework that would aid the decision makers to be logically coherent in modeling their decision policies into respective risk classes to develop a classification predictive model which satisfies the decision makers preferences?

Classification refers to the assignment of a finite set of alternatives into predefined groups. When considering a discrete decision-making problem, there are four different kinds of analysis that can be performed in order to provide meaningful support to decision makers: to identify the best alternative or select a limited set of the best alternatives; to construct a rank-ordering of the alternatives from the best to the worst examples; to classify the alternatives into predefined homogenous groups; and to identify the major distinguishing features of the alternatives and perform their description, based on these features [31]. Choice, ranking and classification lead to specific results regarding the evaluation of alternatives. Classification problems are based on absolute judgments. Each alternative is assigned to a specific group on the basis of a pre-speicified rule. The definition of this rule, usually, does not depend on the set of alternatives being evaluated. For instance, the evaluation result ”product X does not meet the consumer needs” is based on absolute judgments, since it does not depend on the other products that are similar to product X [45]. On the contrary, choice and ranking are based on relative judgments involving pair-wise comparison of the alternatives. Consequently, the overall evaluation result has a relative form, depending on the alternatives being evaluated. For instance, an evaluation result of the form ”product X is the best of its kind” is the outcome of relative judgments, and it may change if the set of products that are similar to product X are altered [12].

An instance of classification problems is the bankruptcy risk evaluation problem [12] in the prediction of firms into healthy and non-healthy firms. This refers to problems where the groups are defined in an ordinal way, since it is obvious that the healthy firms are in a better situation than bankrupt ones. Therefore, classification problems not only provide a simple description of the alternatives, but also incorporate additional preferential information, which could be of interest in the decision-making context. Thus, in classifications, the groups are defined a priori and the analyst knows in advance what the results of the analysis should look like.

Hence, the problem to solve in this research is a classification problem because it incorporates preferential information from decision makers, as the solutions in Papers I, II and III, of Figure 1.1 provide avenues for the incorporation of the preferred risk classes of decision makers, and enables them to become logically coherent in a priori classifications, complemented with formal methods to efficiently develop an accurate predictive classification model that satisfies the preferences of the decision makers.

3. Outline Artifact Requirements

Amongst the numerous methods used for solving multi-criteria classification problems, namely, logit analysis, probit analysis and discriminant analysis, the ELECTRE TRI and UTADIS methods are considered useful and efficient [39]. This is because of the preference disaggregation approach in these two methods which refers to the analysis of global preferences of the decision maker, in order to identify the criteria aggregation model that underlies the preference result. With preference disaggregation analysis, the parameters of the utility decomposition model are estimated through the analysis of the decision makers' overall preference in some reference alternatives. The problem is then to estimate a utility function (usually additive) that is as consistent as possible with the known subjective preferences of decision makers [48].

I considered the UTADIS method in presenting a Multi-Criteria Decision Model for classifying the countries into risk levels of alert and crisis in this research, because-, it only requires a predefined classification of alternatives, in this case, the data on the alternative and criteria relationships and risk classes of the alternatives to be used in the classification of alternatives. Other existing methods in this domain [24][23][26] require as inputs fuzzy information regarding the weights, existing trade-offs and veto thresholds, of which the UTADIS, on the other hand, accurately and efficiently generates and are verified in this research for decision makers instead. The risk classes in the demonstration of the artifact are adopted and validated from an earlier study, conducted by Maplecroft Corporation [21] for the United Nations, which classifies countries into these risk classes but fails to present a country classification decision model as carried out in this research, because the work by Maplecroft Corporation does not analyse data and present the weights on food criteria, as this research does.

Before considering the UTADIS, which is a preference disaggregation approach, alternative approaches for Multi-Criteria Decision Analysis approaches are, namely, Multi Objective Programming [36][41] [37], Multi Attribute Utility theory [28] and outranking relations [31], to mention a few. Compared to these other methods, the preference disaggregation requires the minimal amount of information from decision makers. The weights, trade-offs, reference points, or any other preferential information do not have to be determined a priori by decision makers. Instead, the decision maker, based on his/her past experience is asked to provide some characteristic examples of his decision-making policy through the evaluation of a ”reference” set of alternatives. Then, using ordinal regression techniques, the utility function that has been implicitly used by the decision maker is estimated [47], thus the application of preference disaggregation for this case.

Notable amongst previous research that has studied classification problems for decision makers is the work of Davalos et. al (2009), in the Bankruptcy classification of firms investigated by the US Securities and Exchange Commission [10], in which the authors used an evolutionary computing method and genetic algorithm, to generate an optimal set of if-then rules for bankruptcy classification of Accounting and Auditing Enforcement Release firms, in the prediction of business failure using the UTADIS method [44]. In this study, the authors classify greek sample firms and build a classification model with the UTADIS method in comparison with other methods. Other work by these authors, and others, using the UTADIS method on practical applications, follows the same routine [45] [42] [48][17][18], to cite a few examples of their work. Authors who have applied the ELECTRE TRI method on practical situations have focused their work on the variation of weights of the criteria [24][23][26]. The use of the ELECTRE TRI method in the referenced papers requires the elicitation of parameters (weights, thresholds, category limits,...) in order to construct the decision maker's (DM) preference model. The papers concede that the direct elicitation of these parameters is a rather difficult process, and thus proceed to solve this problem in doubtful ways that require much less cognitive effort, by eliciting these parameters indirectly using holistic information. This is concerned with wholes rather than analysis or separation into parts given by the decision makers through assignment examples, and proposes an interactive approach that infers the parameters of an ELECTRE TRI model from assignment examples. The work in this research would assign accurate weights of the criteria for the decision maker to avoid doubtful ways of eliciting criteria weights.

The work in this present research would present a better application process of the UTADIS method, by introducing the price volatility levels of the countries to model data on the predefined classification process, thus aiding decision makers in making coherent and informed judgments on their preferred risk classes. This would minimise the misclassification errors between the predefined classification process and the original classification, thus enhancing efficiency in the methodological framework. Decision makers in the case of the study in this research would require a method to help them know the volatiltiy information of the food staples in the countries to guide the predefined classification. Moreover, the burden on decision makers, in playing guess games with the weights before arriving at an accurate classification model, as done by other authors stated above using the ELECTRE TRI method, is of less relevance for this research, since the approach in the UTADIS methodological framework works out the required weights of the criteria in the form of an accurate Multi Criteria Decision Model.

4. Design and Develop the Artifact

The Artifact for this research is shown in Figure 4.1 below. It consists of two parts: the first part is a predefined classification represented in the Training set by the symbol ”C”. The second part is the classification algorithm’s (UTADIS) classification, represented by the symbol Ĉ. The following, as explained below, applies to the predefined classification (C):

$A_1, A_2, \ldots\ldots, A_m$ represent the *m* number of alternatives with a value associated with each alternative in the demonstration. The alternatives are the countries at risk of food insecurity.
$g_1, g_2, \ldots\ldots, g_n$ represent the *n* number of criteria food staples.
$C_1, C_2, \ldots\ldots, C_q$ represent the q number of risk classes, with C representing the risk classes of Alert and Crisis.

The UTADIS classification (Ĉ) calculates the following, as explained in the second part of the artifact:

$U_1(\hat{g}_1), U_2(\hat{g}_2), \ldots\ldots, U_n(\hat{g}_n)$ represent the Additive Utility Model or predictive classification model, with U representing the utility or weights of the criteria, $\hat{g}$ representing the criteria and n represents the number of weights and criteria.

$U_{(\hat{g})} = \sum_{i=1}^{n} P_i U_i(\hat{g}_i)$ represents the UTADIS assessment on the global utility $U_{(\hat{g})}$ of an alternative P_i under the criteria $\hat{g}_i$;

$U_1, U_2, \ldots\ldots, U_{q-1}$ are the utility thresholds; always 1 less than the number of risk classes defined in the predefined classification, thus $q - 1$;

$f(\hat{g}) \rightarrow \hat{C}$ represents the whole UTADIS function on criteria $\hat{g}$ to produce the UTADIS classification (Ĉ).

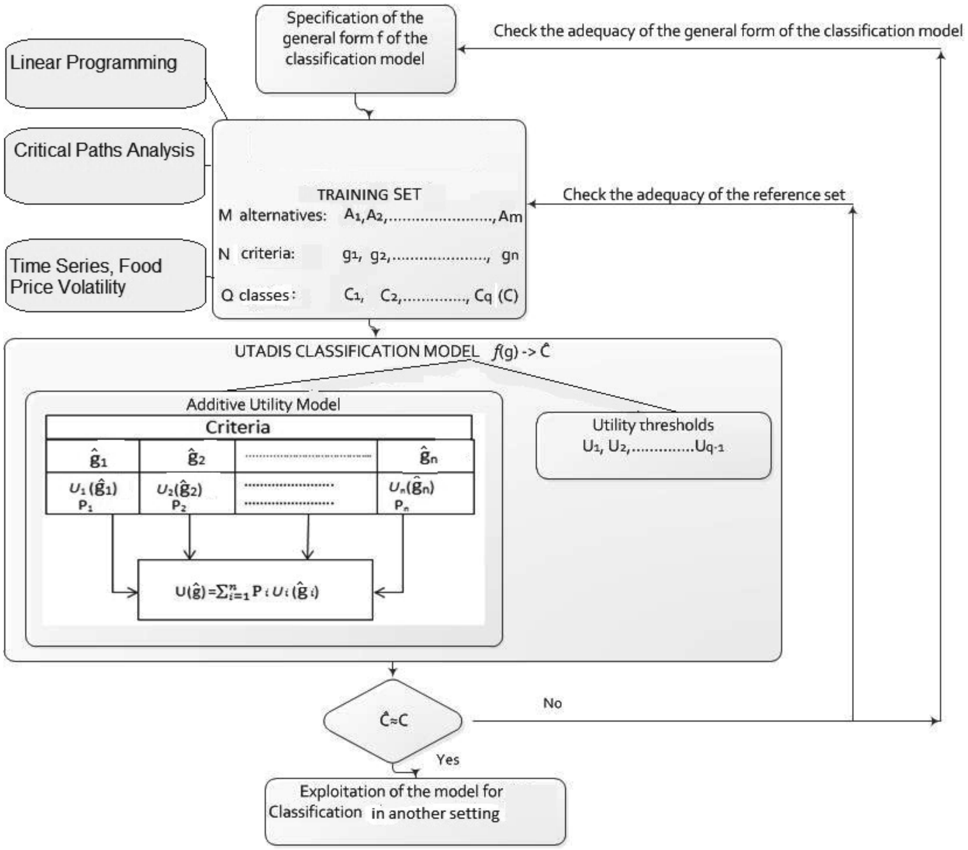

Figure 4.1. The modification of the Artifact with the Data Modeling Methods in the predefined classification to make the Artifact Efficient

In the original work, Zouponidis and Doumpos (2002) [12] (Chp.1 p.18) propose an iterative process in which decision makers iteratively adjust their risk class classification preferences in the predefined classification of Figure 4.1, to match the UTADIS optimization's classification. So, every time the optimization runs, the decision makers would have to make this adjustment, in order to achieve an accurate classification model which is satisfactory. According to this methodological framework, decision makers define their preferences into risk classes in the training set, which is the predefined classification, and interactively adjust it until it matches the classification carried out by the UTADIS optimization: thus an iterative process to achieve a classification model is defined as accurate if it satisfies the criteria data requirements of decision makers in predefining the alternatives into their preferred risk classes, and at the same time matches the UTADIS optimization's classification. The optimization thus uses the data of the preferred classification of decision makers in the predefined classification to carry out its own classification process, and generates a marginal utility function in the form of an additive utility model of criteria weights, which is the classification model. As seen in the framework in Figure 4.1, the ”yes” end of the decision node implies that if there exists, approximately, no misclassification error between the preferred classification of decision makers in the predefined classification and the optimization’s classification, then the resulting marginal utility function or the additive utility model is deemed fit to be the best solution, or the accurate classification model to be used for the classification of new settings. The validation point of the marginal utility function, or additive utility model to be accurate to be used for the classification of new alternatives, is thus where the decision node says ”yes”, as seen in Figure 4.1. This is because at the point ”yes” of the decision node, the classification preferences the decision makers in the training set, or predefined classification, agree with the optimization’s classification, thus the resulting classification model produced by the optimization is the accurate classification model that is satisfactory for decision makers in classifying new alternatives into their preferred risk classes.

However, if the misclassification error is not tolerable, which is where the decision node says ”no”, then decision makers would have to re-adjust the predefined classification repeatedly. Thus, an interactive but iterative process is required until the predefined classification of decision makers matches the optimization’s classification. The aim in this research, is thus to develop an accurate classification model in a very efficient manner, and have it validated by achieving the ”yes” point of the decision node, as shown in Figure 4.1, which implies that the misclassification error is tolerable for the resulting classification model to be a validated one.

4.0.1 Validation of the model

As seen in the framework, the ”yes” end of the decision node implies that if there exists approximately no misclassification error, and the predefined classification matches the optimization’s classification, then the resulting marginal utility function, or the additive utility model, is deemed fit to be the best solution, or the accurate classification model to be used for the classification of new alternatives. The validation point of the marginal utility function, or additive utility model to be accurate to be used for the classification of new alternatives, is thus where the decision node says ”yes”. This is because at the point ”yes” of the decision node, the classification preferences of the decision maker in the training set, or predefined classification, agrees with the optimization’s classification, thus the resulting classification model, produced by the optimization, is the accurate classification model that is satisfactory for decision makers in classifying new alternatives into the decision makers’ preferred risk classes.

4.0.2 Improvements achieved for the Artifact in this thesis

The modification of the UTADIS methodological classification framework to include Data Modeling methods in the predefined classification process, as shown in Figure 4.1, is to make the framework efficient in arriving at an accurate and validated classification model, by executing the framework just once. As demonstrated in Papers I, II and III of Figure 1.1, the process provides more data information on alternative-criteria relationships to aid decision makers in being coherent in applying their subjective preferences to model their alternatives into their preferred risk classes, in the training set or predefined classification. The decision makers are engaged in defining the risk classes, and aided with a supplementary method in the predefined classification to use their judgments and be coherent in modeling data on alternatives into the risk classes.

The aim in this research is to implement data modeling and analysis to aid decision makers in being coherent and to develop the accurate classification model efficiently. Efficiency is achieved by executing the framework just once, and having the classification model validated by achieving the ”yes” point of the decision node. The ”yes” point of the decision node states that the misclassification error should be tolerable for the resulting classification model to be a validated one. This aim is achieved in this research in Papers I, II and III, and propelled by the modification of the work of Zouponidis & Doumpos (2002) [12] (Chp.1 p.18), to include data modeling techniques in the predefined classification, as shown in Figure 4.1. This is imperative because:

1. The data modeling method would model the imprecise time interval data in this research into the required data structure, for the UTADIS method to be able to handle the data in the predefined classification of the methodological framework. Thus the data modeling method is a required supplementary method to aid the work of the UTADIS method in achieving an accurate classification model in this case.

2. The supplementary data modeling method would provide more information to decision makers to aid them in being coherent in modeling the alternative-criteria relationship data, so as to classify the country alternatives into the preferred risk classes of the decision makers.

3. The data modeling in the predefined classification aids the UTADIS optimization in achieving an accurate classification model by executing the methodological framework, just once, for the predefined classification to match with the UTADIS optimization’s classification, thus achieving an accurate classification model in an efficient manner as proven in this research.

4. A further sensitivity analysis is carried out after aiding the decision makers

to be coherent in arriving at the accurate classification model efficiently. As demonstrated in Papers IV and V of Figure 1.1, the sensitivity analysis picks the resulting classification model and aids decision makers in introducing imprecision into the data, by varying the weights in the classification model and ranking the alternatives, so that the decision makers can prioritize which of the alternatives are at high risk, and further identify which criterion is causing the alternatives to be in a high risk zone.

5. Demonstration of the Artifact

As explained in the previous section, the research modifies the classification framework of the Utilities Additives Discriminantes (UTADIS) method thus enhancing the performance of the artifact in producing an accurate classification model in an efficient way. Efficiency is thus introduced in the process of the artifact by executing the framework just once to achieve the accurate classification model. The artifact has its own mechanism for validating the resulting model to be accurate or not, by matching a predefined classification process with the algorithm's resulting classification. The first part of the artifact carries out the predefined classification process, where data modeling is carried out with the objective of satisfying the preferences of decision makers in classifying decision alternatives into risk classes. In contrast to previous research work [45] [42] [48][17][18], this research introduces data modeling techniques to aid decision makers in being coherent in the predefined classification process, and eventually enhancing the operation of the classification algorithm. The data modeling techniques introduced in the predefined classification are thus aimed at supplementing the work of the classification algorithm in efficiently arriving at a predictive and accurate classification model.

5.0.1 The choice of the Classification Algorithm

This research has data on established criteria and alternative relationship and requires a predictive and accurate classification model to aid decision makers in classifying future data sets of the alternatives into the preferred risk classes of the decision maker. The UTADIS classification framework only requires a predefined classification based on data of the alternatives-criteria relationship into risk classes, and then estimates its own utility threshold and global scores of the alternatives. This is achieved by an optimization process that originally classifies the alternatives into risk classes, and then generates weights of the criteria in the form of a marginal utility function, or an additive utility model. Other methods in this paradigm of multi-criteria risk classification would require, prior to the optimization process, sketchy information with respect to the thresholds, weights, and trade-offs from decision makers [20]. Since this research does not require decision makers to struggle with this fuzzy information in carrying out the classification process, but rather has the data on the alternative-criteria relationship, the research thus highlights the UTADIS method as the only appropriate method required to drive the classification process of this research. This section therefore explains the operation of the classification algorithm and how it runs its optimization to carry out its classification process in a piecewise linear process.

5.0.2 Utility Additives Discriminante - UTADIS

"Given a predefined classification of the alternatives into risk classes, the UTADIS method estimates an additive utility function and the utility thresholds that classify the alternatives in their original classes with the minimum misclassification error" [17].

The global utility of an alternative $a_i \in A$ is of an additive form:

$$U(a_i) = \sum_{i=1}^{M} u_i \left[\hat{g}_i(a_i)\right]$$

where $u_i \left[\hat{g}_i(a_i)\right]$ is the marginal utility of the alternative a_i for the criteria $\hat{g}_i$. The marginal utilities represent the relative importance or weight of the evaluation criteria in the classification model. The marginal utilities of the criteria have piece-wise linear form, implying that the value for weights of the criteria is generated with a piece-wise linear process [48]. In the piece-wise linear process, for each evaluation criterion $\hat{g}_i$, with interval $G_i = [\hat{g}_{i*}, \hat{g}_i^*]$, where $\hat{g}_{i*}$ and $\hat{g}_i^*$ are the least and most preferred values, respectively, of the criterion $\hat{g}_i$ for $a \in A$ [43]. The interval G_i is divided into $n_i - 1$ equal intervals, $\left[\hat{g}_i^j, \hat{g}_i^{j+1}\right]$, $j = 1, 2, \ldots, n_i - 1$ where n_i is defined by the decision maker as the number of estimated points for every marginal utility u_i [43]. Each point $\hat{g}_i^j$ can be calculated using linear interpolation [48]. The linear interpolation process in the UTADIS method provides an accurate value in the evaluation of an alternative's score by using breakpoints that have already been defined in the piece-wise linear process

$$\hat{g}_i^j = \hat{g}_{i*} + \frac{j-1}{a_i - 1}(\hat{g}_i^* - \hat{g}_{i*})$$

The aim is to estimate the marginal utilities in each of these points. Supposing that the evaluation of an alternative a on criterion $\hat{g}_i$ is $\hat{g}_i(a) \in \left[\hat{g}_i^j, \hat{g}_i^{j+1}\right]$, the marginal utility of an alternative a, $u_i \left[\hat{g}_i(a)\right]$ can be approximated through linear interpolation [48] in the following way:

$$u_i \left[\hat{g}_i(a)\right] = u_i(\hat{g}_i^j) + \frac{\hat{g}_i(a) - \hat{g}_i^j}{\hat{g}_i^{j+1} - \hat{g}_i^j} \left[u_i(\hat{g}_i^{j+1}) - u_i(\hat{g}_i^j)\right] \tag{5.1}$$

Supposing that the preferences of the decision maker on each one of the evaluation criteria are monotone, the following constraint must be satisfied [43]:

$$w_{ij} = u_i(\hat{g}_i^{j+1}) - u_i(\hat{g}_i^j) \geq 0, \forall i, j$$

Monotonic preference implies that the decision maker prefers a greater satisfaction in terms of the marginal utility of a criteria for an alternative, therefore $u_i(\hat{g}_i^{j+1}) - u_i(\hat{g}_i^j)$ should remain positive at least. If it becomes negative, the resulting weight of the criteria being considered would be less and that would impact negatively, that is, it would produce a lesser total score for the asset, which is the alternative under consideration.

The monotonicity constraints can be converted into non negativity constraints through the following transformations [43]. The idea of non negativity constraints is to restrict the decision variables to positive values, or a minimum of zero

$$u_i(\hat{g}_{i*}) = 0$$

$$u_i(\hat{g}_i^*) = \sum_{k=1}^{n_i-1} w_{ik}$$

$$u_i(\hat{g}_i^j) = \sum_{k=1}^{j-1} w_{ik}$$

where $\sum_{k=1}^{j-1} w_{ik}$ is the summation of the marginal utilities of the breakpoints for the piecewise linear process $u_i(\hat{g}_i^j)$.

Equation 5.1 can therefore be re-written as follows:

$$u_i\left[\hat{g}_i(a)\right] = \sum_{k=1}^{j-1} w_{ik} + \frac{\hat{g}_i(a) - \hat{g}_i^j}{\hat{g}_i^{j+1} - \hat{g}_i^j}\left[\sum_{k=1}^{j} w_{ik} - \sum_{k=1}^{j-1} w_{ik}\right] \tag{5.2}$$

5.0.3 The misclassification errors

The misclassification error is deduced from [C - Ĉ], as shown in Figure 4.1. The UTADIS optimization calculates the global utility of the alternatives in the predefined calculation, and generates the cut-off points or the utility thresholds [48]. The global utility is then compared with the utility thresholds, placing the alternatives into an appropriate risk class. The UTADIS classification into risk classes is then compared with the classification into risk classes of the preferences of the decision maker [48], and if an alternative's classification in the UTADIS classification does not match the alternative's classification in the decision maker's preferences, then it is judged a misclassification error.

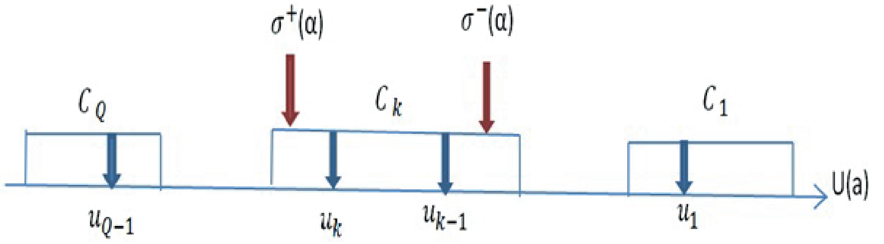

Figure 5.1. Distribution of the classes on the assessed utility

In Figure 5.1 above, u_k, u_{k-1}, u_{Q-1} and u_1 represent utility threshold points generated by the UTADIS optimization, C_Q, C_K and C_1 represent the risk classes, and $U(a)$ is the global utility of an alternative. Thus, if the alternative, according to the preferences of the decision maker in the predefined classification, should belong to a high risk class C_1, and the UTADIS classification after comparing the global utility of the alternative $U(a)$ with the utility thresholds place the alternative in a lower risk class C_Q, then it is judged as an error, and that the alternative has been underestimated. Likewise, if the alternative, according to the preferences of the decision maker in the predefined classification, should belong to a low-risk class C_Q, and the UTADIS classification, after comparing the global utility of the alternative $U(a)$ with the utility thresholds places, the alternative in a higher risk class C_1, then it is judged as an error, and that the alternative has been overestimated.

Overestimation error $\sigma^-(a)$: it is where an alternative according to its utility is classified to a higher risk class than the risk class that it belongs to, C_Q, as shown in Figure 5.1.

Underestimation error $\sigma^+(a)$: it is where an alternative according to its utility is classified to lower risk class than the risk class that it belongs to, C_1, as shown in Figure 5.1.

The classification of the alternatives is achieved through the comparison of their global utilities, with the corresponding utility thresholds [43]

$$U(a) \geq u_1 \rightarrow a \in C_1$$

$$u_k \leq U(a) < u_{k-1} \rightarrow a \in C_k$$

$$U(a) < u_{Q-1} \rightarrow a \in C_Q$$

The assessment of both the marginal utilities $u_i\left[\hat{g}_i(a)\right]$ and the utility thresholds u_k is achieved by linear programming [43]. I use linear programming, because, with the combination of the variables and constraints in the decision problem, I want to achieve the least misclassification error possible, as shown in the objective function below:

$$Minimize \quad F = \sum_{a \in C_1} \sigma^{+}(a) + \ldots + \sum_{a \in C_k} \left[\sigma^{+}(a) + \sigma^{-}(a)\right] + \ldots + \sum_{a \in C_Q} \sigma^{-}(a)$$

$\sum_{a \in C_1} \sigma^{+}(a)$ sums up all the overestimated errors for alternatives in the highest class;

$\sum_{a \in C_Q} \sigma^{-}(a)$ sums up all the underestimated errors for alternatives in the lowest class;

$\sum_{a \in C_k} \left[\sigma^{+}(a) + \sigma^{-}(a)\right]$ sums up both the overestimated and underestimated errors for alternatives in the intermediate risk class.

The objective function thus minimizes the misclassification errors, which are the overestimated and the underestimated errors in the defined risk classes of the decision maker, according to the constraints below, outlined one by one and clarified.

$$\sum_{i=1}^{m} u_i\left[\hat{g}_i(a)\right] - u_1 + \sigma^{+}(a) \geq 0 \quad \forall a \in C_1$$

The first constraint above ensures that with all the variables for an alternative that belong to the highest risk class C_1, the global utility of an alternative should not be equal to the utility threshold u_1 with its overestimation error, which placed the alternative in risk class C_1 [48]. Thus, the subtraction of the utility threshold with its overestimated error $\sigma^{+}(a)$ from the value of the global utility of an alternative should always be greater than zero for all alternatives that falls into the highest risk class C_1.

$$\sum_{i=1}^{m} u_i\left[\hat{g}_i(a)\right] - u_{k-1} - \sigma^{-}(a) \leq -\delta$$

$$\sum_{i=1}^{m} u_i\left[\hat{g}_i(a)\right] - u_k + \sigma^{+}(a) \geq 0$$

$$\forall a \in C_k$$

In the second constraints, σ is a small positive real number used to ensure the strict inequality of the global utility, or global score $U(a)$ to the utility thresholds u_{k-1} ($\forall a \in C_k, k > 1$), and $u_{Q-1}(\forall a \in C_Q)$. The constraint $\sum_{i=1}^{m} u_i\left[g_i(a)\right] - u_{k-1} - \sigma^{-}(a) \leq -\delta$ ensures a strict inequality of the global utility of an alternative $U(a)$ in an intermediary risk class C_k to the intermediary threshold u_{k-1}, by introducing a small positive real number δ, such that when the threshold value is added to an underestimated error and subtracted from the global utility of an alternative, there would still be a value remaining [48]. In other words, when the δ, which is negative on the right side of the equation, is moved to the left side of the equation, it becomes a positive real number, which then adds up to the value of the global utility of the alternative, ensuring that the utility threshold never equals the global utility of the alternative.

The constraint in the gathered constraints:

$$\sum_{i=1}^{m} u_i\left[\hat{g}_i(a)\right] - u_k + \sigma^{+}(a) \geq 0$$

also complies by ensuring the global utility of an alternative, with all the variables under consideration, does not equal the utility threshold u_k

$$\sum_{i=1}^{m} u_i\left[\hat{g}_i(a)\right] - u_{Q-1} - \sigma^{-}(a) \leq -\delta \quad \forall a \in C_Q$$

The third constraint above implies that for the least utility threshold u_{Q-1}, with all alternatives in the lowest risk class C_Q, when the global utility of an alternative is impacted with the δ value, this should ensure the strict compliance to the rule that the global utility of the alternative is not equal to the utility threshold u_{Q-1}, with its underestimated error $\sigma^{-}(a)$

$$\sum_{i=1}^{m} \sum_{j=1}^{n_i-1} w_{ij} = 1$$

The constraint restricts all the sum, of the marginal utilities or weights of the variables in the decision-making problem to be equal to 1, with w_{ij} representing the weights of all the criteria, m represents the number of criteria

$$u_{k-1} - u_k \geq s \quad k = 2, 3 \ldots Q-1$$

$$w_{ij} \geq 0, \sigma^{+}(a) \geq 0, \sigma^{-}(a) \geq 0$$

where δ is a small positive real number used to ensure the strict inequality of $U(a)$ to u_{k-1} $(\forall a \in C_k, K > 1)$, and $u_{Q-1}(\forall a \in C_Q)$. In Figure 5.1 above, $u_{k-1} > u_k$, with k representing the levels of threshold, thus a lower k level has a higher threshold than a higher k level. Thus s is the difference when a higher k level of utility threshold is subtracted from a lower k level, which has a higher utility threshold. The threshold s is thus used to denote the preference between the utility thresholds that distinguish the classes $(s > \delta > 0)$. It is reasonable to say that δ, which is just a small positive real number used to ensure the strict inequality of the global utility of an alternative to a utility threshold, to allow for risk classification, should be lesser than the strict preference between the closest utility thresholds of u_{k-1}, and u_k. s should also be greater than zero, since the preference between two thresholds should be greater than zero, otherwise there would be no preference at all, and, moreover, subtracting a lower threshold from a higher threshold should obviously not be less than, or equal to, zero. The δ value should also be greater than zero, so that the global utility of an alternative can be classified into a risk class hovering over a utility threshold. A delta value of zero would set the global utility of an alternative equal at a utility threshold, thus making it impossible to classify the alternative.

5.0.4 Case for the demonstration

The United Nations (UN) and Development Partners are working on Sustainable Development Goals, with the objective of eliminating worldwide poverty. The sustainable development goals have diverse components which the United Nations seek to achieve and strategise in indicators, so as to mitigate against countries plunging into poverty, in the long run, as the UN monitors individual projects to achieve the objectives of the sustainable development goal. Monitoring a project's performance and outcomes provides avenues for effective control mechanisms for all procedures in any phase of the project, and helps identify risky stages or indicators in the project which require attention in keeping the projects on track and schedule. Identifying project distress and mitigating against project failure in such humanitarian initiatives is very vital in saving lives and curtailing the cost of investments, because the failure of such projects can have very dire consequences, not only for the United Nations but the global economy as a whole. Particularly, developing economies are vulnerable, as these low-income regions would face harsh consequences. Also, considering the globalization of the world economy, it is obvious that the vulnerabilities in the developing economies would have replicating consequences for developed nations as well, because more resources would have to flow in the direction of the developing nations, obviously from the developed world. This calls for a look into how to safeguard vulnerable economies from the effects of shocks in the sustainable development goals.

Governments seek the welfare of their citizens by providing basic amenities. The United Nations has as one of its objectives in the sustainable development goals to help Governments provide affordable lives for their citizens. As part of its objectives, the global body has set up targets for between 1990 and 2015 to halve the proportion of people whose income is less than $1.25 a day, to achieve full and productive employment and decent work for all including women and young people, and, finally, between 1990 and 2015 to halve the proportion of people who suffer from hunger [13]. The United Nations thus spends a considerable amount of resources in this direction to help Governments secure food access for its citizens. Project failure, or distress in any of these initiatives, would thus have detrimental consequences, not only for the UN but for investors and partners as well, who are striving with the UN to eliminate worldwide poverty.

The UN and Development Partners have indicators or criteria for the projects which overlap, and are not integrated for strategic decision making. This, therefore, calls for criteria aggregation models which would reveal the risk level of criteria, and integrate these and criteria risk levels in decision-making processes. In this way, projects and countries can be well-separated into risk classes for the sustainable development goals. Furthermore, suitable risk models would be generated which would aid the UN in predicting the countries or projects into their preferred risk classes, in the long run, as the projects progress and require monitoring. There is therefore a decision-making problem for the UN to classify the projects in the sustainable development programme on risk levels. The UN are interested not only in classifying projects according to risk levels, but would want to have clear information regarding what the actual risks of individual projects are. With the data on criteria available from the UN and the Development partners, this decision problem would require a classification scheme which would solve the uncertainty situation in the overlapping criteria of the projects, and present a forecast of the risk levels of the projects to the UN for strategic decision making. This demonstration of the artifact therefore presents predictive classification mechanisms in the form of criteria aggregation models, which would satisfy the objectives of the decision makers at the United Nations in their drive to eliminate worldwide poverty through the sustainable development goals.

Uncertainty in the decision-making criteria was sensitive to the sustainable development goals adopted by the UN. This presented a problem in designing an appropriate classification framework for decision makers to develop a classification model. The model would inculcate imprecise data and uncertainties in the criteria to help decision makers strategise against failure of the sustainable development goals, and help them represent their preferences and decision policy. The aim of this study was therefore to develop risk assessment models which would present a decision strategy for predicting countries which would fall into risk classes in order to mitigate project risks. This would entail a predefined classification process, whereby countries were classified into risk classes based on available data regarding the criteria. The risk classes represent different groups outlining danger or comfort for a country or project. I, therefore, had the aim of developing an accurate model to classify the countries into the risk categories, considering the preferences of decision makers in an efficient manner, regarding which country should fall into which risk class, based on available data relating to the objectives of the sustainable development goals. The resulting model can then be used for monitoring purposes, without having to conduct large surveys.

There are countries which feel secure today, in terms of the UN sustainable development goals at the macro level. However, there is still some insecurity if countries lack some components of the sustainable development goals at the micro level, thus risking a deterioration of the country's risk class, over time, for the sustainable development goals. The implication is that the standards set out in the sustainable development goals by the UN should be consistently fulfilled over time, to reduce, or eliminate, the risk of countries falling below the standards of the sustainable development goals. The availability, or adequate supply, of resources at national or international levels would not, in itself, provide an assured household-level security. Recently, concerns about insufficient access to basic life amenities have resulted in a greater policy focus on incomes, expenditure, markets and prices in achieving sustainable development goals objectives. Chronic resource shortages due to inadequate financial resources or economic planning can be overcome with long-term development measures, such as decision strategies for policy makers to have predictive mechanisms for sustainable development goals. Talking about the need for predictive mechanisms arises from the fact that countries can be vulnerable to sudden shocks in global economic fluctuations in the future, even if the country is currently not exposed to economic shocks. Vulnerability to sustainable development goals is thus presented from the view point of a variety of risk factors and the inability to manage those risks.

Research conducted by Maplecroft [21] has troubling revelations which indicate that as much as the UN body would want to put in place measures to secure global Governments for providing basic welfare services for its citizens, as stated in the sustainable development goals, uncertainties in worldwide data on components of the sustainable development goals can upset the efforts and investments made by the UN, due to the fragility of the world economy. It has therefore become imperative to develop reliable criteria aggregation models which would aid the United Nations and Governments in predicting countries which fall into risk classes, so as to strategise and achieve the objectives of sustainable development goals. The different criteria defined by the UN are tagged with different data types and involve uncertainties that are not integrated, thus presenting a big decision problem. This demands a methodological approach which would incorporate uncertainties in the different criteria, and which is flexible enough to accept future data in presenting a robust prediction model for country-wise risk classification.

6. Evaluating the Artifact – Analysis, Findings and Discussion

This study has identified methods for data modeling in the artifact. The aim is to aid decision makers in being coherent in classifying alternatives into their preferred risk. Furthermore, the work has the objective of introducing efficiency into the decision-making processes, and aims at developing an accurate predictive classification model. The model is used for the prediction of future data sets into the preferred risk classes of decision makers.

6.0.1 Data Analysis

A data-driven process with the flexibility to incorporate the preferences of decision makers, and derive weights of criteria, utility thresholds and global scores of alternatives to build a classification model is implemented in this research. This is necessitated by the fact that the case study presents decision variables on alternatives with price uncertainties that are not integrated, and, as such, presents a big challenge for decision makers to be coherent in developing a classification predictive model in an efficient manner. This obviously calls for methods delving into data analysis to solve uncertainty problems in decision making, which would integrate all the decision variables and present a robust predictive classification model for decision makers, while flexible enough to incorporate the preferences of decision makers as well, as shown in Papers I, II and III. Also, keeping in mind the cost of wasting time in the decision-making processes, it becomes imperative that the research adopts an approach that would efficiently aid the decision makers in arriving at an accurate classification model. Software tools, such as MATLAB and R-Studio, were used in programming the methods for data analysis, and Java was used for the interface that derives the results of the data analysis processes. It is worth noting that apart from the artifact, which has a means of judging the accuracy of the classification model and the classification generated by the optimization, the data analysis results from the MATLAB tool also confirmed the accuracy of our results for the research.

Figure 6.1 below is the Java interface which extracts the data analysis results from the use of the MATLAB tool, after the optimization process is carried out.

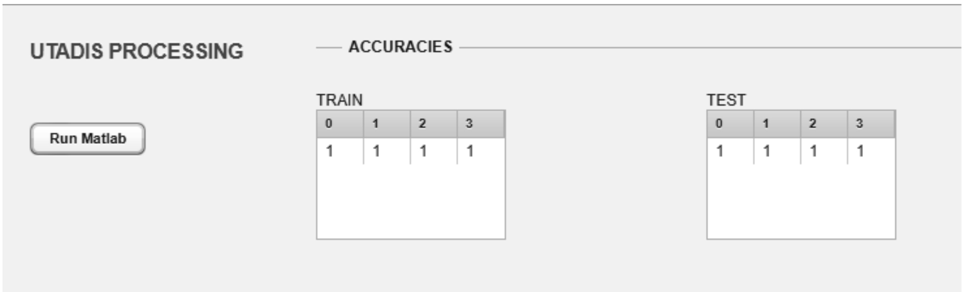

Figure 6.1. Data showing the accuracy level of the classification in both the Training and Testing data set

Figure 6.1 shows the accuracies of the results of the classification process in Papers I, II and III. All 1's imply a hundred percent accuracy for both the train and test data sets for the classification in the predefined classification, and the original classification after the UTADIS optimization's classification. This accuracy level is thus not only depicted by the classification artifact framework, which I modified to be made efficient in this research, but also the data analysis revealed by the MATLAB tool furthermore buttressed our findings that this research indeed achieved an accurate classification model for aiding decision makers in being coherent, thus injecting efficiency into the classification framework. Papers IV and V also provided avenues for decision makers to analyze and introduce variations in data for relativity in criteria and alternative data, to enable decision makers rank the alternatives for prioritization purposes.

As shown in the Java interface in Figure 6.2 below, which extracts the criteria weight values from MATLAB and visualizes it, I am able to aid decision makers in analyzing the risk level of the criterion and advise management on decision-making processes to adapt, in order to mitigate against the risk posed to the decision making process, as explained in the conclusions of Papers I, II and III.

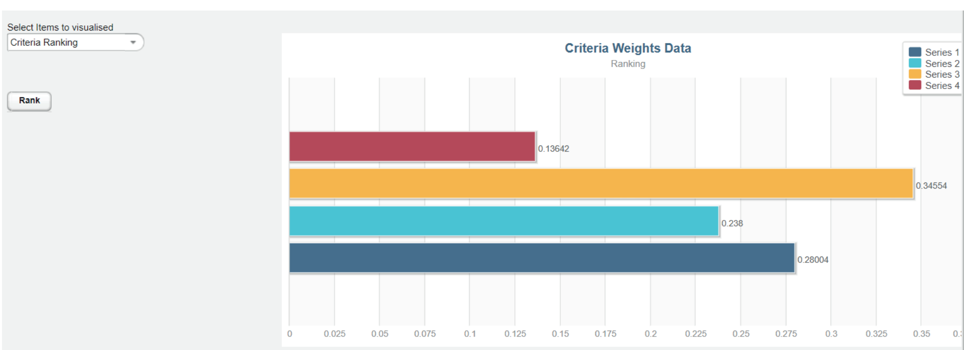

Figure 6.2. Figure showing the data sensitivity of the accurate weights of the criteria for the research

A sensitivity analysis process is carried out on these weights in Papers IV and V, as part of the contribution of this research, to vary the weights due to future data alterations, and is later discussed in this section.

The data analysis approach adopted derives from the fact that-, a more tangible means of advising decision makers on the risk of classification is imperative in asserting some guidelines in the predefined classification process, which is originally a subjective process and leads to several iterations in the methodological classification framework before an accurate classification model is achieved. Thus the data analysis approach provides us not only with the ability to examine the risk levels of the criteria, as seen in Papers I, II and III, but also to analyze the accuracy levels with the data, as explained above, thus solidifying my findings of providing an accurate classification model in an efficient way. The contribution of introducing methods to aid decision makers in being coherent in the data modeling of the predefined classification solves uncertainty problems in the data for the predefined classification, so that the classification algorithm can handle the data in conducting its original classification, thus generating the classification model efficiently.

6.0.2 Data Modeling

I contributed in this research to the quality of the data modeling process in the predefined classification of the classification framework or artifact, in order to aid decision makers in being coherent in achieving an accurate classification model in an efficient manner. The quality of data modeling in the predefined classification is of essence, because it defines the amount of time that decision makers would have to devote to arriving at a quality decision regarding an accurate classification model. The modeling procedure in Papers I, II and III adopted methods which would, first of all, re-structure the data, so that the classification algorithm can handle the data input from the predefined classification. Secondly, it provides adequate information on the objective of the classification process for decision makers aiding them to be coherent and make informed judgments on the predefined classification modeling. This would further help the decision makers to be efficient in arriving at an accurate classification model. Some of the data modeling techniques implemented in the predefined classification making the classification artifact efficient for this research include the following:

Linear Programming

In Paper I, imprecision [15] in criteria data values had to be resolved, so as to provide room for the classification algorithm to accept input data from the predefined classification. Linear Programming [24][23] was identified for the data modeling, because it could calculate the project profit as an objective, and at the same time, decide on selecting the lower or upper boundary of the criterion's data imprecision, based on the coefficient of the alternative's value tag attached to a criterion. Thus, the linear programming calculated the project's profit value of informed decision-making processes for decision makers to be coherent [27], and modeled the alternatives into their preferred classes, restructuring the imprecise data on the criteria for the classification algorithm to handle the input data from the predefined classification of the classification framework [45] [42]. It is realized from this data modeling process in Paper I, that the research restructured the data for the classification algorithm, considering imprecision in all the criteria values as an alternative. The research arrived at an accurate classification model depicting the risk level of the criteria with just one execution of the classification framework, therefore achieving the aim of research.

Critical Path Analysis

In Paper II, the project's time frame with data on overlapping activities had to be resolved for decision makers to be able to classify the alternatives into preferred risk classes. The only data modeling method that could handle this problem is the critical path analysis method [40]. This method accesses the risk of project failure in a time frame to reveal the critical paths in the projects. The critical paths method also restructures the raw data from the project time frames, so that the classification algorithm can accept the project data as critical paths. The critical paths analysis revealed the slack times in the activities for the projects, which allows for flexibility of time in delivering on an activity in the project. The method also reveals the high-risk activities in a project, which require a high level of attention to be delivered, because failure to deliver on such high-risk activities in a project could result in the failure of the project as a whole. The number of critical paths in the projects were thus used as information to aid decision makers in being coherent [27] in modeling the project data in the predefined classification of the classification algorithm [45] [42]. The critical paths information is also used to restructure the data from the project time line as input data for the classification algorithm. The algorithm then runs an optimization that calculates the global scores of the project alternatives and utility threshold, and carries out an original classification. An accurate prediction model is then generated, in the form of a marginal utility function which consists of the weights of the criteria, with just one execution of the framework. The predefined classification matched the classification of the algorithm, implying an accurate prediction model according to the design of the framework. I am thus able to identify the correct data modeling method for making the algorithm efficient in arriving at an accurate predictive model, thus achieving the aim of the research.

Time Series-Price Volatility

In Paper III, of utmost importance in the data modeling process is analyzing price data over a time period [5]. This aids decision makers in being coherent [27] in building a predictive classification model for volatility. In sampling the price data on food staples criteria in relation to country alternatives over a time period, decision makers would want to mitigate against the risk of food price escalation. Food price escalation would have an adverse effect on economic planning policies of countries, because development plans are often based on consumer prices. Price fluctuations [33] would, thus, make it a herculean task for decision makers to continuously readjust development plans to suit fluctuating consumer prices with time. This calls for a strategic predictive classification model which would consider the long-term effects of fluctuating consumer prices to aid decision makers in fashioning out policies for food security. I identified the time series method [5] as the only suitable method to be applied to calculate the price volatility of the food criteria. Furthermore, the method provides information to aid decision makers in modeling the data into preferred risk classes, and to have a structured data which would serve as input data for the classification algorithm [45] to build a predictive classification model on food price volatility. The data restructuring is imperative for the classification algorithm to consider all the time interval, in the criteria food prices, not leaving out any detail in the data ranges. This further presents a fair assessment of the price variations in the time considered to be important in the evaluation process. R-programming is thus used to calculate the price volatility information from the time series data. The total price volatility for an alternative is aggregated and used to aid decision makers in being coherent in modeling the alternatives into preferred risk classes. This ascertains a justifiable line of reasoning as input information aiding the decision makers to arrive at a classification model, which inculcates their preferences, and, at the same time, is robust enough to withstand price data fluctuations over time. The classification in the algorithm matched the predefined classification modeled with information from the time series price volatility, implying an accurate predictive model is achieved.

6.0.3 Sensitivity Analysis

The validation of the classification model or marginal utility function to be accurate by means of the classification framework, and supported by the accuracy values of the MATLAB tool in Papers I, II and III, provided me with encouragement to do some variation on the weights of the criteria in the predictive classification model in Papers IV and V, as I am assured that the decision maker is happy with the accuracy level of the classification model in its predictive power. The idea of the sensitivity analysis is to introduce imprecision [8][6] in the decision-making process, and to judge the criteria sensitive [38] enough to alter the position of the countries in an ordinal ranking. A two-part sensitivity analysis is considered, consisting of a manual and automated sensitivity analysis.

In the manual sensitivity analysis, as carried out in Paper IV, a scale is used by the decision maker to access the relative importance [8] of the criteria with regards to the weights in the classification model or marginal utility function, enabling the decision maker to establish known differences in the relative importance of the criteria, by using the scale values to generate a mixed model for ranking the alternatives. This gives the opportunity to compare the criteria to each other, and to know how much, or less, importance the different criteria have when compared to each other on a scale. The scale has peculiar values marked from ”much less important” to ”much more important”. Thus, depending on the value of the weight of the criteria being compared from the classification model, the decision maker is able to judge the importance level of one criteria compared to another. This empowers decision makers in assigning a relative value from the scale and in producing a table matrix which has relative values of the criteria from the scale. The resulting table matrix values are then normalized to provide a fair assessment for the relative values of the criteria, with a row-wise average for each criteria. The weights of the criteria at this stage provide a mixed model, which is further used on the relative values of the alternatives to conduct an ordinal ranking of the alternatives. The relative values of the alternatives are also analyzed by re-engineering the modeled alternative-criteria data in the predefined classification into expected values of the alternatives. New value functions of the alternatives are then defined by multiplying the average normalized criteria values with the expected values of the alternatives, and then aggregating the values to produce an overall score of the alternatives for ordinal ranking.

In Paper V, a second-stage sensitivity analysis is carried out. An automated risk analysis tool, DecideIT [9], gives the decision maker the flexibility to vary the weights of the criteria and alternative values. As information comes to managers in a vague form with imprecision in real-world situations [6], DecideIT provides decision makers with an avenue to inject as much imprecision as decision makers want, considering all the possibilities available for data alteration in the decision-making process. The accurate weights generated from the classification algorithm are thus modeled in a multi-criteria decision tree, and variation is carried out to consider the possibilities of the impact of price volatility on the weights of the criteria. The DecideIT tool also provides the opportunity of varying the alternative values, based on a ”most likely point” which is varied to a minimum interval and a maximum interval. An ordinal ranking of the alternatives is then carried out with imprecision in both the criteria and alternative values. The results of the ranking with DecideIT produced some interesting similarities, compared to results of the ranking carried out with the manual sensitivity analysis. The findings of the sensitivity analysis revealed the same top-two positions for both the manual and automated sensitivity analysis, thus, I found it interesting to find out the most sensitivity criteria [38] which could alter the position of these top-two alternatives.

7. Conclusions

Improving the functional efficiency of a classification decision support system for coherency for decision makers in achieving an accurate risk classification prediction model is the main aim of this research. The decision support system constitutes the artifact, as defined by design science. The research thus focuses on the improvement of the functional performance of the classification decision support system. The artifact is a two-part classification methodological framework which requires a predefined classification of alternatives into risk classes as defined by decision makers, and then runs an optimization classification algorithm in the second part, to conduct its original classification, accepting input data from the predefined classification. The research introduces efficiency into this classification framework by aiding the decision makers in being coherent and in modeling the data in the predefined classification with data modeling techniques, thus enhancing the performance of the classification framework to produce an accurate classification predictive model with just one iteration of the classification framework.

Data for the case study of the research consists of yearly food prices, in US dollars, for countries, and is obtained from the United Nations Food and Agricultural Organization. The food criteria have been identified and decided upon by the United Nations to be very essential for food security for some identified countries. Data is of the imprecise format, and thus data modeling techniques are used to re-structure the data, so that the classification algorithm can handle the data. The data modeling methods further aid decision makers in modeling the alternatives in the predefined classification of the framework by providing adequate information to the decision makers. This information equips decision makers with much-needed guidelines and supports their experiences in being coherent when modeling the data of alternatives into their preferred risk classes. It is realized in this research that by supplementing the work of the classification algorithm with a data modeling method in the predefined classification of the classification framework, data clarity is achieved for decision makers in being coherent and in providing an insight into how to model the alternatives in the predefined classification, backed with their experiences, and an accurate classification predictive model is achieved by just one iteration of the classification framework, thus saving time for decision making. The accuracy of the predictive model is validated by the classification framework and also the accuracy values, as shown in the MATLAB tool. The advantage of choosing the artifact or classification framework used in this research is that it has an inbuilt testing mechanism to validate the resulting predictive classification model in being accurate. Thus, it does not require to test the predictive classification model any further to prove its accuracy, once the testing mechanism in the classification framework has validated the predictive classification model to be accurate.

After achieving the accurate predictive classification model, a manual and automated sensitivity analysis is carried out to vary the weights of the criteria in the predictive classification model. As real-life situations demand, data comes in vague forms, and thus decision makers are provided with some flexibility in generating relative values for the criteria by means of a scale, guided, of course, by the weights in the classification predictive model. The relative values of the alternatives are generated and then an ordinal ranking is carried out by calculating the global scores of the alternatives from the relative values of the criteria and alternatives. An automated risk analysis software, which gives the decision maker the flexibility to introduce as much imprecision as possible into the decision-making process, is also used to rank the alternatives, and some similarities are realized in the ranking of the manual and sensitivity analysis. The research also revealed the most sensitive criterion which is likely to change the positions of the alternatives. It is hoped that the findings in this research will serve as a basis for policy formulation for the United Nations in mitigating the risk of failure of the sustainable development goals.

7.0.1 Future Research

For future research, the approach in this research will be extended to other countries which perform better for food price volatility and develop models with sensitivity analysis. This will provide decision-makers with more information on the sensitivity of criteria in these countries,for decision-makers to be equipped with more strategies to aid the countries in this research mitigate against food security risk. Furthermore, the integration of tools which handle imprecise data with the UTADIS classification framework will be explored to provide the artifact with more functional power.

References

[1] W Baumol. *Business behavior, value and growth*. New York, Macmillan, Princeton University, Princeton, NJ, 1959.

[2] Vanita Bhoola. Impact of project success factors in managing software projects in india: An empirical analysis. *Business Perspectives and Research*, 3(2):109–125, 2015.

[3] C. Busso. *Multimodal Analysis of Expressive Human communication: Speech and Gesture Interplay*. PhD thesis, University of Southern Carlifornia, 2008.

[4] Carlos Busso, Sungbok Lee, and Shrikanth Narayanan. Using neutral speech models for emotional speech analysis. In *INTERSPEECH*, 2007.

[5] Mei Yuan Chen. *Time Series Analysis: Conditional Volatility Models*. McGraw-Hill, New York, 2013.

[6] J. Corner and P.D. Corner. Characteristics of decisions in decision analysis practice. *Journal of the Operational Research Society*, 46:304–314, 1995.

[7] M. Cummings, J. Marquez, and N. Roy. Human-automated path planning optimization and decision support. *International Journal of Human-Computer Studies*, 70(2):116–128, Feb. 2012.

[8] Mats Danielson and Love Ekenberg. Cardinal rank ordering for multi-criteria decisions. *World Scientific Proceedings Series on Computer Engineering and Information Science*, 2(7):2, 2012.

[9] Mats Danielson, Love Ekenberg, Jim Johansson, and Aron Larsson. The DecideIT decision tool. In Jean-Marc Bernard, Teddy Seidenfeld, and Marco Zaffalon, editors, *ISIPTA*, volume 18 of *Proceedings in Informatics*, pages 204–217. Carleton Scientific, 2003.

[10] Sergio Davalos, Fei Leng, Ehsan H. Feroz, and Zhiyan Cao. Bankruptcy classification of firms investigated by the US Securities and Exchange Commission: An evolutionary adaptive ensemble model approach. *International Journal of Applied Decision Sciences*, 2:360 – 388, 2009.

[11] Janne M. Denolf, Jacques H. Trienekens, P.M. (Nel) Wognum, Jack G.A.J. van der Vorst, and S.W.F. (Onno) Omta. Towards a framework of critical success factors for implementing supply chain information systems. *Computing Industry*, 68(C):16–26, April 2015.

[12] M. Doumpos and C. Zopounidis. *Multicriteria Decision Aid Classification Methods*, volume 73 of *Applied Optimization*. Springer, Formerly Kluwer Academic Publishers, Boston, Dordrecht, London, 2002.

[13] United Nations Millenium Development Goals. We can end poverty, millenium development goals and beyond 2015 @ONLINE, September 2013.

[14] Shirley Gregor and Alan R. Hevner. Positioning and presenting design science research for maximum impact. *Management of Information Systems Quarterly*, 37(2):337–356, June 2013.

[15] Min Guo, Jian Bo Yang, Kwai-Sang Chin, Hong-Wei Wang, and Xin Bao Liu. Evidential reasoning approach for multiattribute decision analysis under both fuzzy and interval uncertainty. *Transactions on Fuzzy Systems.*, 17(3):683–697, June 2009.
[16] Muhammad Mustafa Hassan, Andr□s Moreno, Erkki Sutinen, and Abdul Aziz. Supporting participatory innovation through introductory tools. In Brian Donnellan, Markus Helfert, Jim Kenneally, Debra VanderMeer, Marcus Rothenberger, and Robert Winter, editors, *New Horizons in Design Science: Broadening the Research Agenda*, volume 9073 of *Lecture Notes in Computer Science*, pages 479–487. Springer International Publishing, 2015.
[17] E. Jacquet-Lagreze. An application of the UTA discriminant model for the evaluation of sc R and D projects. In P. Pardalos, Y. Siskos, and C. Zopounidis, editors, *Advances in Multicriteria Analysis*, Nonconvex Optimization and its Applications, pages 203–211. Kluwer Academic, Dordrecht, 1999.
[18] E. Jacquet-Lagreze and J. Siskos. Assessing a set of additive utility functions for multicriteria decision-making, the uta method. *European Journal of Operational Research*, 10(2):151–164, 1982.
[19] Loic Kessous, Ginevra Castellano, and George Caridakis. Multimodal emotion recognition in speech-based interaction using facial expression, body gesture and acoustic analysis. *Journal on Multimodal User Interfaces*, 3(1):33–48, 2009.
[20] Rueben Laryea. A multi-criteria prediction model for project risk classifications. *International Journal of Decision Sciences, Risk and Management, 5(1):55-79*, 2013.
[21] maplecroft Global Risk Analytics. Maplecroft's food security risk index 2013 @ONLINE, September 2013.
[22] Salvatore T. March and Gerald F. Smith. Design and natural science research on information technology. *Decis. Support Syst.*, 15(4):251–266, December 1995.
[23] V. Mousseau, J. Figueira, and J. Ph. Naux. Using assignment examples to infer weights for electre tri method: Some experimental results. *European Journal of Operational Research*, 130(2):263–275, 2001.
[24] V. Mousseau and R. Slowinski. Inferring an ELECTRE TRI model from assignment examples. *Journal of Global Optimization*, 12(2):157–174, 1998.
[25] Allen Newell, J.C. Shaw, and H.A Simon. Empirical explorations with the logic theory machine: A case study in heuristics. In *Proc. Western Joint Computer Conference*, volume 15, pages 218–239, 1957. Reprint: Feigenbaum and Feldman, Computers and Thought, 1963, luger.
[26] A. Ngo The and V. Mousseau. Using assignment examples to infer category limits for the ELECTRE TRI method. *JMCDA*, 11(1):29–43, November 2002.
[27] Andrea Polonioli. The uses and abuses of the coherence □ correspondence distinction. *Frontiers in Psychology*, 6:507, 2015.
[28] Keeney R. and Raiffa H. *Decisions with Multiple Objectives*. Cambridge University Press, Cambridge, U.K., ISBN 0-521r-r43883-7., 1993.
[29] Michael Röder, Andreas Both, and Alexander Hinneburg. Exploring the space of topic coherence measures. In *Proceedings of the Eighth ACM International Conference on Web Search and Data Mining*, WSDM '15, pages 399–408, New York, NY, USA, 2015. ACM.

[30] Martin Rogers and Michael Bruen. Choosing realistic values of indifference, preference and veto thresholds for use with environmental criteria within electre. *European Journal of Operational Research*, 107(3):542–551, 1998.
[31] B. Roy. *Méthodologie multicritère d'aide à la décision*, volume 1er Ed of *Collection Gestion: Série, production et techniques quantitatives appliquées à la gestion*. Économica, 1985.
[32] Angel Mart□nez Sanchez and Manuela P□rez P□rez. Early warning signals for r&d projects: An empirical study. *Project Management Journal*, 35(1):11–23, 2004.
[33] Pasquale Scaramozzino. Measuring vulnerability to food insecurity. *ESA Working Paper No. 06-12, Agricultural and Development Economics Division, The Food and Agriculture Organization of the United Nations*, 4(06), 2006.
[34] Dan Simon, Lien B. Pham, Quang A. Le, and Keith J. Holyoak. The emergence of coherence over the course of decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 27, 2001.
[35] R. Slowinski and C. Zopounidis. Application of the rough set approach to evaluation of bankruptcy risk. *International Journal of Intelligent Systems in Accounting, Finance and Management*, 4(3), 1995.
[36] J. Spronk. *Interactive Multiple Goal Programming: Applications to Financial Planning*. Martinus Nijhoff Publishing, Boston, 1981.
[37] R. E. Steuer. *Multiple Criteria Optimization: Theory, Computation and Application*. John Wiley, New York, 1986.
[38] E. Triantaphyllou. *Multi-Criteria Decision Making Methods: A Comparative Study*. Applied Optimization. Springer, 2000.
[39] J. Wang. Multi-criteria classification approach with polynomial aggregation function and incomplete certain information. *Journal of Systems Engineering and Electronics*, 17(3):546–550, 2006.
[40] Jerome D. Wiest and Ferdinand K. Levy. *A management guide to PERT/CPM / Jerome D. Wiest, Ferdinand K. Levy*. Prentice-Hall, Englewood Cliffs, N.J., 1969.
[41] M. Zeleny. *Multiple Criteria Decision Making*. McGraw-Hill, New York, 1982.
[42] C. Zopounidis. Multicriteria decision aid in financial management. *European Journal of Operational Research*, 119(2):404–415, 1999.
[43] C. Zopounidis and M. Doumpos. Developing a multicriteria decision support system for financial classification problems: The FINCLAS system. *Optimization Methods and Software*, 8(3-4):277–304, 1998.
[44] C. Zopounidis and M. Doumpos. Business failure prediction using the utadis multicriteria analysis method. *Journal of the Operational Research Society (JORS)*, 50(11):1138–1148, 1999.
[45] C. Zopounidis and M. Doumpos. Multi-criteria decision aid in financial decision making: Methodologies and literature review. *Journal of Multi-Criteria Decision Analysis*, 11(4-5):167–186, 2002.
[46] C. Zopounidis, Ch. Hurson, and M. Doumpos. *Risque-Pays: Evaluation des Aspects Economiques, Sociaux et Politiques*. Economica, Paris, 2000.
[47] Constantin Zopounidis. Preference disaggregation in financial modeling: Basic features and some examples. *Operational Research*, 1(3):263–284, 2001.
[48] Constantin Zopounidis and Michael Doumpos. A multicriteria decision aid

methodology for sorting decision problems: The case of financial distress. *Computing Economics.*, 14(3):197–218, December 1999.