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Multiple Criteria Decision Making in Application Layer Networks

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Contents

List of Figures

List of Tables

List of Abbreviations

AHP	Analytical Hierarchy Process
ALN	Application Layer Network
BDI	Belief-Desire-Intention
CAGR	Compound Annual Growth Rate
CIS	Catallactic Information System
DBA	Digital Business Agent
DM	decision-maker
DPS	Distributed Problem Solving
EbA	Elimination by Aspects
ELECTRE	ELimination Et Choix Traduisant la REalité
eRep	Social Knowledge for e-Governance (project acronym)
EU	European Union
EUR	Euro
Euro NCAP	European New Car Assessment Programme
FPSB	first-price sealed-bid
g	gram(s)
GB	gigabyte
ICT	information and communication technology
IDB	Impressions Database
IVD	Ideal Vector Database
km	kilometer
kmph	kilometer per hour
LM	Lexicographic Method
LS	Lexicographic Semiorder
Ltr	liter
MAS	Multi Agent System
MADM	Multiple Attribute Decision Making
MCDM	Multiple Criteria Decision Making
MODM	Multiple Objective Decision Making
ODB	Outcomes Database
PD	Partner Database

PDF ....Portable Document Format
PROMETHEE... Preference Ranking Organization METhod for Enrichment Evaluations
PRS..Procedural Reasoning System
RON .... Research Octane Number
sec...second(s)
SAW .... Simple Additive Weighting
SDB .... Sociograms Database
TOPSIS.........................Technique for Order Preference by Similarity to Ideal Solution
UML ....Unified Modeling Language
xTOPSIS...... Extended Technique for Order Preference by Similarity to Ideal Solution

List of Symbols

Φ .... Preference function
a_{ij} .... Outcome of alternative *i* for criterion *j*
A_i .... Alternative *i*
A .... Decision matrix (bold printed)
C .... Criteria comparison matrix (bold printed)
c_{ij} .... Relative importance of criterion *i* versus criterion *j*
C_j .... Criterion *j*
Con .... Concordance matrix
con_{kl} .... Concordance index for alternative *k* compared to alternative *l*
d_i .... Deviation variable for objective *i* (in Goal Programming)
Dis .... Discordance matrix
dis_{kl} .... Discordance index for alternative *k* compared to alternative *l*
E .... Dominance matrix
$f_i(x)$ .... Linear function (for objective *i*) of alternative *x* (in Goal Programming)
F .... Concordance dominance matrix
G .... Discordance dominance matrix
IM_i .... Image value of seller of offer *i*
m .... Number of criteria
n .... Number of alternatives
nw_i .... Weight of negative deviation for objective *i* (in Goal Programming)
pw_i .... Weight of positive deviation for objective *i* (in Goal Programming)
PR_i .... Price of offer *i*
q .... Number of objectives (in Goal Programming)
R_i .... Similarity to ideal solution of alternative *i*
S .... *is at least as good as* (Outranking relation)
S_i .... Distance index of alternative *i*
SR_i .... Social reputation value of seller of offer *i*
t_i .... Target value (goal) for objective *i* (in Goal Programming)
V .... Decision matrix with evaluated outcomes (bold printed)
v_i .... Partial value of *i*

V_i .... Aggregate value of i
w .... Weight vector (bold printed)
w_j.. Weight j
x... Alternative (in Goal Programming)
z.. Achievement function (in Goal Programming)

1 Introduction

1.1 Starting Position: Trust in eCommerce

The rise of the *Internet economy* can be attributed to the worldwide spread of Internet access points and the rapid pace of ICT development (*information and communication technology*), which together induced cross-border networking between private households, enterprises and entire markets [Wirt01, 23–25]. The Internet economy paved the way for *electronic Commerce* (eCommerce) and enabled traditional enterprises to move parts of their value chain online [Wirt01, 40]:

According to Eurostat, the Statistical Office of the European Communities, the turnover share from eCommerce has soared by a compound annual growth rate of 26 percent during the past three years (Figure 1) [Euro08a]. For the next three years, market analysts of Forrester Research as well as eMarketer even predict a vigorous annual growth of 21 to 25 percent for the European business-to-customer market [Forr08], [Emar08].

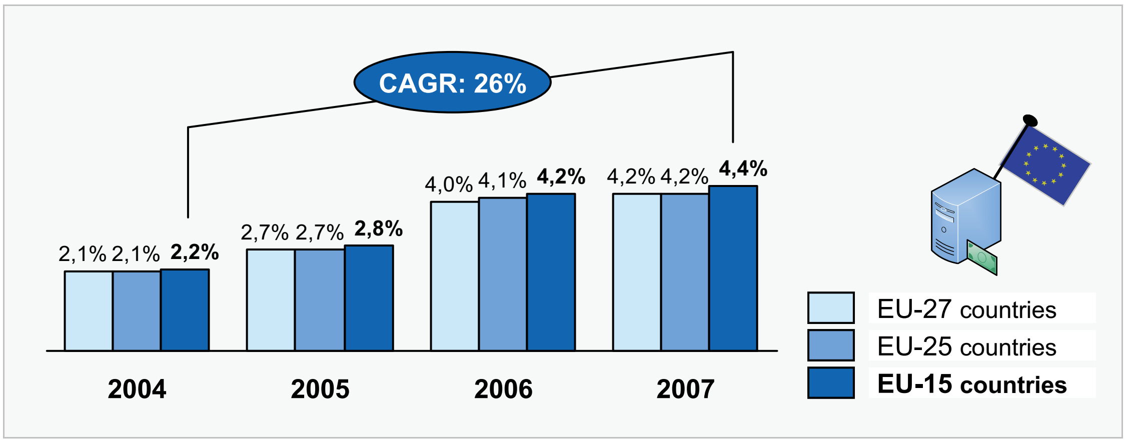

Figure 1: Percentage of EU enterprises' total turnover from eCommerce via Internet [Euro08a]

But the increasing number of customers and suppliers also bears risks:

Since Internet traders are dispersed worldwide and may remain anonymous, it is difficult to estimate the trustworthiness of a potential partner upon the first encounter [BoOc06, 1], [RZSL06, 80]. In consequence of doubts and mistrust, honest partners refrain from trading while fraudulent ones continue, which eventually leads to destruction of markets for high quality goods [Aker70]. Currently, one of eight Europeans shies away from shopping online due to lack of trust in digital stores [Eur08b, 1].

On their search for cure, electronic institutions (e.g. the popular electronic markets *Amazon Marketplace*, *eBay*, and *Yahoo!Shopping*) discovered *reputation systems* (also called *online feedback mechanisms*). Their purpose: Building trust between strangers by disseminating ratings from past encounters [Amaz08], [Ebay08a], [Yaho08], [Erep05, 3–4], [Dell03, 1407].

But how can we explain online reputation systems in the light of social cognitive theory, i.e. how is reputation generated, spread and represented? Is there a standard mechanism, or how shall we engineer a reputation system to fulfill its purpose as good as possible? These questions are the core issues of the *Social Knowledge for e-Governance* (eRep) project sponsored by the EU's *Framework Programme for Research and Technological Development*. After laying the theoretical foundations and developing a reputation mechanism, the project committee plans to implement this mechanism in an *agent*-based environment and test the impact of the reputation system [Erep05, 2–4], [Euro02a, 2].

The actors in the specified simulation scenario, multiple software agents trading with each other, consider the reputation of potential partners in their course of negotiations. The goal of this study is to determine an efficient method for programming this consideration step.

1.2 Objectives of this Study

In the simulation scenario of the eRep project, multiple agents contemplate reputation of potential partners before purchasing goods. The primary objective of this work is the elaboration of an appropriate procedure for decision-making, i.e. a method for preparing decisions by processing information (e.g. price, reputation) and providing a clear advice to the agent.

Aside from the distinct method, we keep the following secondary objectives in mind:

1. Trading services: The progress from trading plain digital goods (such as music files, *Video-on-demand*) to renting software applications leads to a multitude of distinguishing features [StEy07, 7], [Back03, 379], [MEKr03, 298–299], [ShVa99, 55–63]. Can the chosen decision-making method cope with all additional requirements and enable the automated trade of complex goods?

2. Added benefit: Are there any added benefits that can be drawn from the application of the chosen method?
3. Restrictions: Modeling the scenario and implementing the decision-making method involves necessary concessions in terms of assumed underlying connections. Which assumptions inhibit the translation of the scenario results to human-based environments?

1.3 Conduct of this Study

Our search for an appropriate decision-making method is based on a scenario similar to the simulation testbed of the eRep project (Figure 2). Thus we explain underlying theories of this scenario and characterize the environment and its determinants.

The latter enables us to derive prerequisites for developing a framework of our decision-making problem. Where possible we will point out connections to developments of the eRep project to assure the outcome of this work can be finally transferred to the simulation testbed (Section 2).

Thereafter we conduct an analysis of eleven methods for multiple criteria decision problems and sort the results according to their requirements. In connection with the inspection, we examine fundamentals of modeling decision problems, namely *data scaling* and *preference integration* (Section 3).

Section 4 summarizes and synthesizes the results of the previous sections. The elaborated prerequisites enable us to detail the specifications of the simulation scenario, which in turn allow us to recommend a particular decision-making method. We modify and demonstrate this technique using a numerical example and close with a summary of our findings.

The work ends with a summary comprising of answers to the questions we have posed above. Moreover, we list potential opportunities of the chosen method and provide recommendations for further research on decision-making in the given context (Section 5).

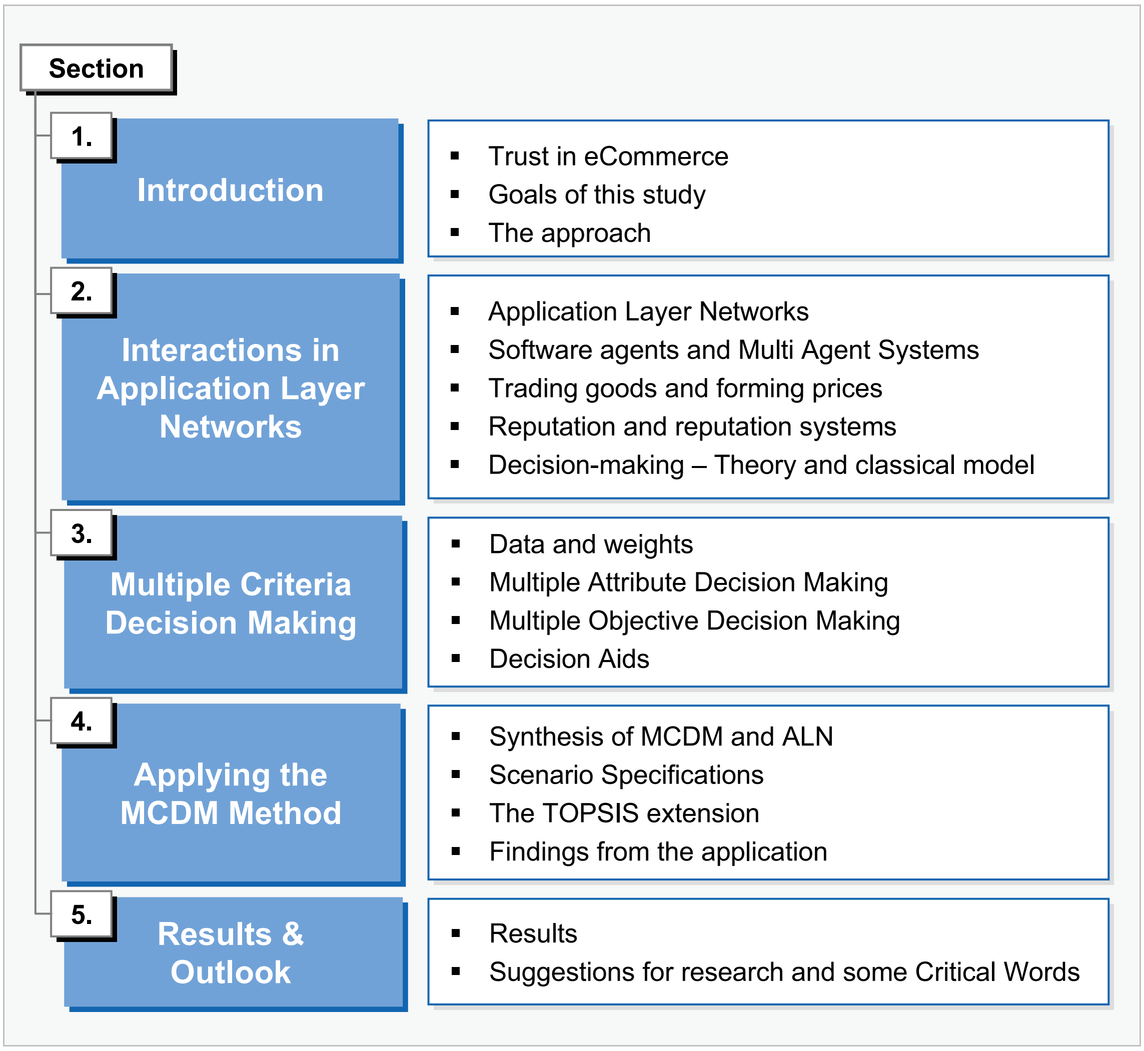

Figure 2: General approach of this work

The Appendix at the end includes the example of a multiple criteria decision problem concerning the purchase of a car. The case study complements the work in terms of illustrating the calculation steps for almost all presented decision-making methods.

2 Interactions in Application Layer Networks

2.1 Depicting the Environment

This Section clarifies the used terminology and describes the economic environment in which the decision-making scenario is located (Figure 3). To achieve that, we explain the coordination principle (Subsection 2.2) and present the actors (Subsection 2.3). Thereafter, we clarify the rationale for and the conduct of interaction (Subsection 2.4) before we attend to the function of reputation in general and as an inherent institution of the environment (Subsection 2.5). Finally, we explicate decision-making and glance at preference modeling (Subsection 2.6).

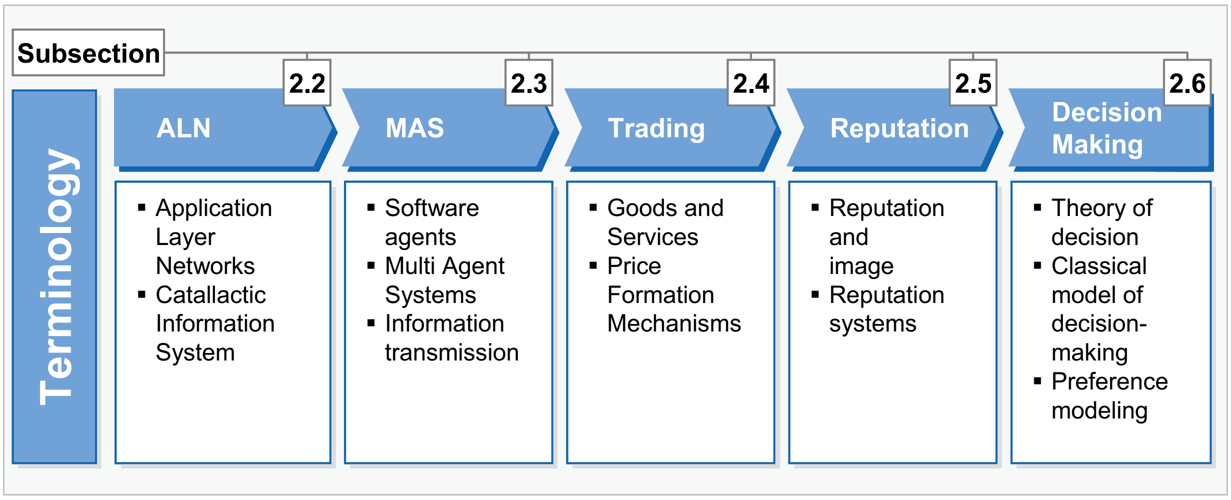

Figure 3: Outline of the 2nd Section

2.2 Coordination in Application Layer Networks

2.2.1 Application Layer Networks

An extensive computer network which provides services requiring a considerable amount of resources is called *Application Layer Network* (ALN). In order to acquire these resources, ALNs use communication infrastructures such as the *Internet* in order to interconnect numerous individual computers [ESR+05, 7].

Resource allocation by means of centralized mechanisms proves to be inefficient for two reasons: First, the coordinating institution is supposed to transfer instantly a huge number of requests from connected peers. Second, rapidly changing member structures in dynamic networks and multiple varying environmental states place great demand on the processing capacities of the coordinator. Especially large-scale networks call for coordination mechanisms which are capable of allocating resources and services in real time to fulfill specified service-levels [ERA+04, 10], [Eyma03, 53–54]. Hence, we explain a decentralized philosophy in the next Subsection.

A prominent example for an ALN is the Peer-to-Peer system *BitTorrent* which enables members to share resources and transfer files to each other [SNV+07, 91–92], [Cohe03, 1]. For the application of ALNs in academics, prime examples are the Stanford University's *Folding@home* project or the distributed search for extra-terrestrial intelligence, *SETI@home*, run by the Space Science Laboratory at the University of California, Berkeley [Pand08, 1-2], [Univ08].

In the scenario of this work, the ALN is a *virtual hard disk* composed of space provided by linked up computer systems (Figure 4).

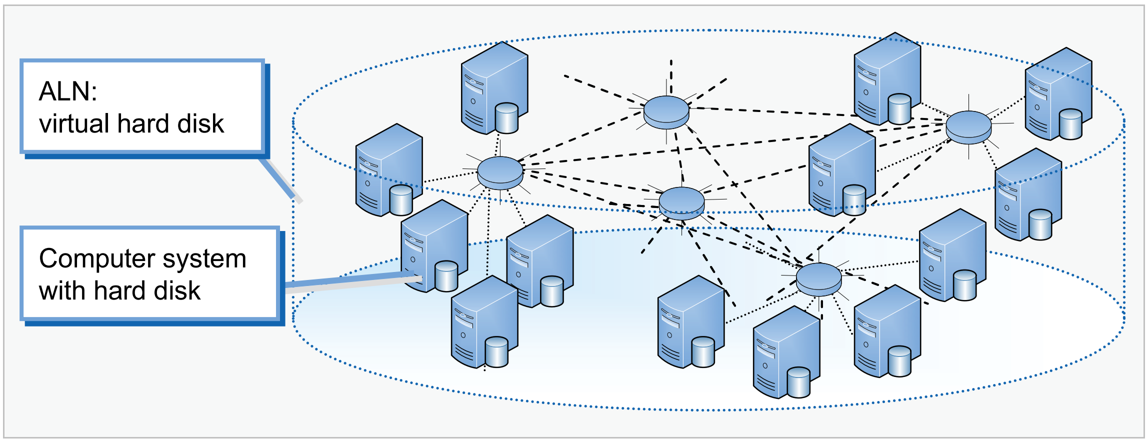

Figure 4: The ALN as a virtual hard disk

2.2.2 Catallactic Information Systems

With regard to the economic principles of Friedrich August von Hayek's *Catallaxy*, the *Catallactic Information System* (CIS) proposes a decentralized coordination mechanism as a new paradigm for the design of information systems [EPSc00, 349–350].

Hayek's Catallaxy can be understood as a synonym for free-market economy, using prices as coordination mechanisms and, without knowledge of the individual actors' behaviors, leading to a "spontaneous order" [Eyma03, 157]. The concept assumes members in the system are self-interested and strive to maximize their utility. As participants can neither foresee future market states nor predict other agents' behaviors (*constitutional ignorance*), they are forced to make decisions under *bounded rationality* [ESR+05, 13]. The CIS molds the concept of Catallaxy using the technology of *Multi Agent Systems* (MAS), which consist of software agents representing the actors in the Catallaxy (cf. Subsection 2.3.2).

The evaluation of a Catallaxy-based coordination mechanism has been subject to research in the *CATNETS* project. The authors deduced several fields for further research, including, but not limited to, the necessity to implement electronic institutions and social control mechanisms to cope with volatile service qualities and malevolent software agents [StEy07, 27–30]. With respect to these findings we implement a governance mechanism in our future scenario.

2.3 Software Agents in Multi Agent Systems

2.3.1 Software Agents

2.3.1.1 Agents in Computer Science

The Merriam-Webster explains the term *agent* as "one who is authorized to act for or in the place of another", i.e. a representative of someone or something [Merr08a, § 4]. The translation of the traditional meaning in the context of computer science is called *software agent* or *intelligent agent*. Due to the versatility of agents in applications, a definite and overarching explication is still open [Burk03, 1014–1015], [Nwan96, 208].

Referring to Wooldridge, we understand software agents as *autonomous* entities interacting with their environment in a bidirectional way: Agents receive input through sensors and use effectors to react with output *actions* [Wool00, 29].

In addition to autonomy, our agents are *intelligent* in the sense that they are *flexible* in conducting actions to achieve their goals. Flexibility in turn comprises the following three features:

- *reactivity* refers to immediate response to environmental changes,

- *pro-activeness* is the ability to take the initiative, and
- *social ability* means interacting with other agents.

Each feature has implications for the remainder of this work: Social ability requires the presence of additional agents to cooperate with as well as the implementation of a common communication language. Pro-activeness and reactivity seem contradictory, and reactivity even puts autonomy into question – in order to balance these features, an internal model is required that allows elaborating and adjusting plans of action [Wool00, 32–33].

Supplementary to Wooldridge's definition of reactivity, suggestions for further potential dimensions are listed in [Burk03, 951–953]. Nwana takes up *learning* which evolves from past interactions with the environment, and argues for its explicit consideration [Nwan96, 210]. Learning is "any instance of improvement of behavior through increased information about the environment" [Kael93, 4]. Though learning seems implicit when attributing reactivity to agents, it can take various forms in MAS; a general characterization can be found in [SeWe00, 260–264].

In our context, the agent learns from encounters with others in the way that he adjusts his beliefs about the environment.

2.3.1.2 Practical Reasoning in the Internal Model

Between *perception* and *action*, the internal model provides the basis on which agents make decisions and fulfill their assigned function. *Practical reasoning* is the two-phase process of *deliberation* and *means-end reasoning*. At first, deliberation refers to deciding *what* state to achieve, whereas means-end reasoning afterwards refers to deciding *how* to achieve the particular state. States an agent has committed to are called *intentions*: they drive means-end reasoning, constrain future deliberation, and exert influence on beliefs [Wool05, 66–69].

Among the available models, we will outline the *Procedural Reasoning System* (PRS) in the following paragraphs, since it is an approved implementation for deliberate agents and embodies the *Belief-Desire-Intention* (BDI) paradigm [Wool05, 82]. Farther, the PRS corresponds to the framework used in the eRep project [SPV+07, 13].

In the PRS architecture, four attitudes determine the behavior of the agent, i.e. how practical reasoning is conducted. Our agent is in possession of the key data structures *beliefs, desires, intentions* and *plans* (Figure 5) [Wool96, 663–664]:

- *Belief*: knowledge emerging from information about environmental states received and updated through the agent's sensor. Belief is subjective and not necessarily correct or complete.
- *Desire*: objectives or tasks, the agent is supposed to accomplish, and priorities associated with them. Desire represents the motivational state of an agent.
- *Intentions*: deliberative state. Intentions are the currently chosen course of action, i.e. the objective the agent has committed to pursue at the moment.
- *Plans*: particular patterns of instructions to achieve an objective. Plans are made up of a goal, a context (preconditions) and a body (the sequence of actions to carry out).

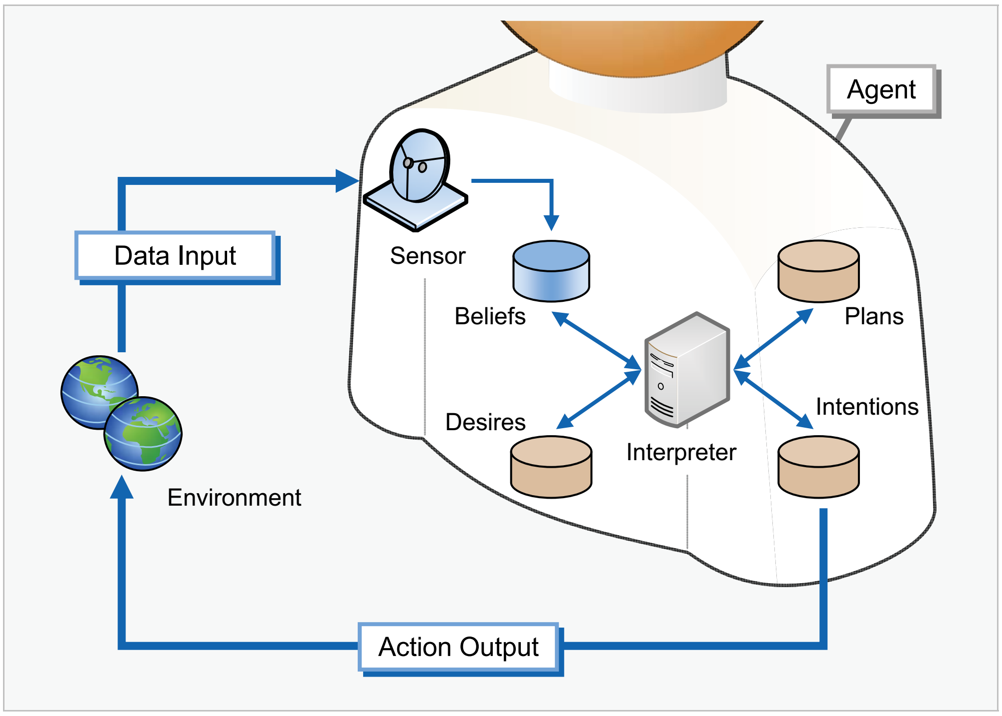

Figure 5: The Procedural Reasoning System [Wool05, 83]

The process of procedural reasoning works as follows: At the beginning, the interpreter (planner) has beliefs about the world, a collection of plans and a top-level goal. He browses his library of plans to extract those ones that match both goal and precondition of the current state. Afterwards, in the process of *deliberation* the agent selects a plan from the resulting *set of options*. A practical means to allow rational justified selections is the implementation of a *utility value* for options: then the plan with the highest value is selected (for an explication of utility cf. Subsection 2.6.4). After execution of the chosen plan, new goals arise and require deliberation and so on. [Wool05, 83–84].

2.3.1.3 Digital Business Agents

Software agents acting on behalf of a legal entity in commercial environments are called *digital business agents* (DBA). They are obedient, utilitarian entities whose commercial function (goal) is defined by a *principal* (human being or organization). Obedience implies that the DBA's paramount goal is always aligned with the principal's one: to act in the owner's interest. This in turn justifies the utilitarian attitude of the agent, expressed by rational conduct in order to contribute to the principal's utility [Eyma03, 24–26].

Roughly, one may distinguish between two different cases in which DBAs are used: the *cooperative* and the *competitive* environment (Table 1).

Table 1: Standard cases for the employment of DBAs (based on [Eyma03, 27])

Paradigm	**Cooperation**	**Competition**
Pursued Goals	Common Collective utility maximization (e.g. low cycle time)	Conflicting Individual utility maximization (e.g. high profit)
Environment	Closed system Number of participants is constant	Open system Agents enter and leave the system during runtime
Number of agents per principal	Multiple	One
Example	Product design	Procurement

This work assumes a competitive environment, since this corresponds with the CIS underlying the ALN and the research subject of the eRep project. At present, possible purposes of DBAs include capacity management, supply chain coordination, product design, and trade on electronic marketplaces [Eyma03, 99–107]. This work will focus on the decision-making process of DBAs trading on an electronic marketplace.

2.3.2 Multi Agent Systems

Discussing how various agents interact with each other involves explaining how coordination is realized between them. On the one hand we have cooperation through

Distributed Problem Solving (DPS), on the other hand competition is solved through *negotiation* processes (Table 2) [HuSt00, 83]. While in DPS a common goal is fractured *top-down* and solved *bottom-up*, MAS have the top goal emerging from the bottom as a result of the various agents' competing goals [Eyma03, 49–51].

Table 2: Distinction between DPS and MAS [RoZl98, 15–16]

	DPS	**MAS**
System designing	Centralized	Decentralized
Coordination Paradigm	Cooperation: Agents **cooperate** to achieve the common goals	Competition: Agents **negotiate** with each other
Pursued Goals	Common	Conflicting

In accordance with the concept of DBAs, participating agents in MAS are rational, self-interested and utility-maximizing; they strive to realize the interest of their respective owner [RoZl94, 31]. Thus, DBAs negotiate with each other in order to achieve their goals.

As mentioned before (cf. Section 2.2.2), the implementation of the CIS constitutes a price mechanism to encourage coordination between the rival agents. Assuming that we apply the MAS idea to an electronic marketplace, we predict the overarching goal is system efficiency in terms of a Pareto efficient allocation of traded goods with their respective utility (*welfare maximization*) [Vari06, 618–620], [RoZl94, 31].

2.3.3 Disseminating and Gathering Information

With the implementation of reputation (cf. Subsection 2.5.1.2), it becomes necessary to compute an aggregate which reflects the common image of the target agent. We assume agents disseminate their experiences on a voluntary basis, though this contradicts with the definition of the self-centered, utilitarian agent (cf. Subsection 2.3.1.3). Miller et al. suggest a complex reward system based on scoring rules to elicit honest feedback from other participants [MRZe05]. For the sake of simplicity, we suppose agents spread information on a voluntary basis.

In order to allow dissemination and accumulation of information in the ALN, a formal communication mechanism has to be implemented. Possible forms range from *broadcasting* mechanisms over *blackboard* systems to *direct* communication

[Eyma03, 56–58]. Whereas broadcasting means transmitting information to all participants ("one-to-many"), direct communication relates to the opposite channel-wise messaging ("one-to-one"). Blackboard systems store news (feedback) in repositories and disseminate information upon request; well-known eCommerce examples include online reputation systems such as the ones of *Amazon Marketplace*, *Ebay*, or *Yahoo!Shopping* [Amaz08], [Ebay08a], [Yaho08]. Researchers of the eRep project have also examined possible means of communication and their effects on reputation [CoPa07, 9–13]. Despite the high degree of decentralization of our reference system, we presume agents store data partially in public local repositories which are accessible for all connected members when requesting information (Subsection 2.5.2.3).

2.4 The Object of Interaction: Trading Goods

2.4.1 Homogeneous and Heterogeneous Goods and Services

In ordinary language, *goods* are "something that has economic utility or satisfies an economic want" [Merr08b]. Moreover, we need to differentiate goods with respect to their impact on marketing: While some goods do not allow differentiation and further market segmentation, some goods permit multi-dimensional customization. Thus, the following terminology is being used from now on: When we talk about goods, we mean goods *and* services. Very complex, multi-faceted goods which can hardly be compared are named *heterogeneous* goods (e.g. cars, advisory, holiday trips), while very simple goods, which only differ in their price, are called *homogeneous* goods (e.g. power, coal or storage capacity in megabytes) [WRSc05, 69], [GLFo04, 257].

These two types of goods can be understood as extreme values on a continuum – many goods are positioned in between. To determine the grade of complexity, we use the typology of Woratschek and classify goods on three dimensions: behavioral uncertainty associated with the transaction, the degree of customer integration and the degree of customization [WRSc05, 69], [Wora96, 69]. We can illustrate the continuum between homogeneity and heterogeneity using a sliced cube (Figure 6).

A distinction between homogeneous and heterogeneous goods is applicable in ALNs as well: the former are termed *resources*, the latter *services*. Moreover we assume application services (e.g. converting a *Portable Document Format* file [PDF]) can be broken down into resources needed to provide the service (like hard disk capacity and processing power) [StEy07, 7–8].

We hold on to a commodity or plain resource (such as a coal or wheat) and assume sellers cannot modify the good in a way that allows them to differentiate from competing suppliers. From a customer's perspective, all offers are equal except for the price and the potential supplier (uncertainty about the suppliers' trustworthiness is a distinguishing feature).

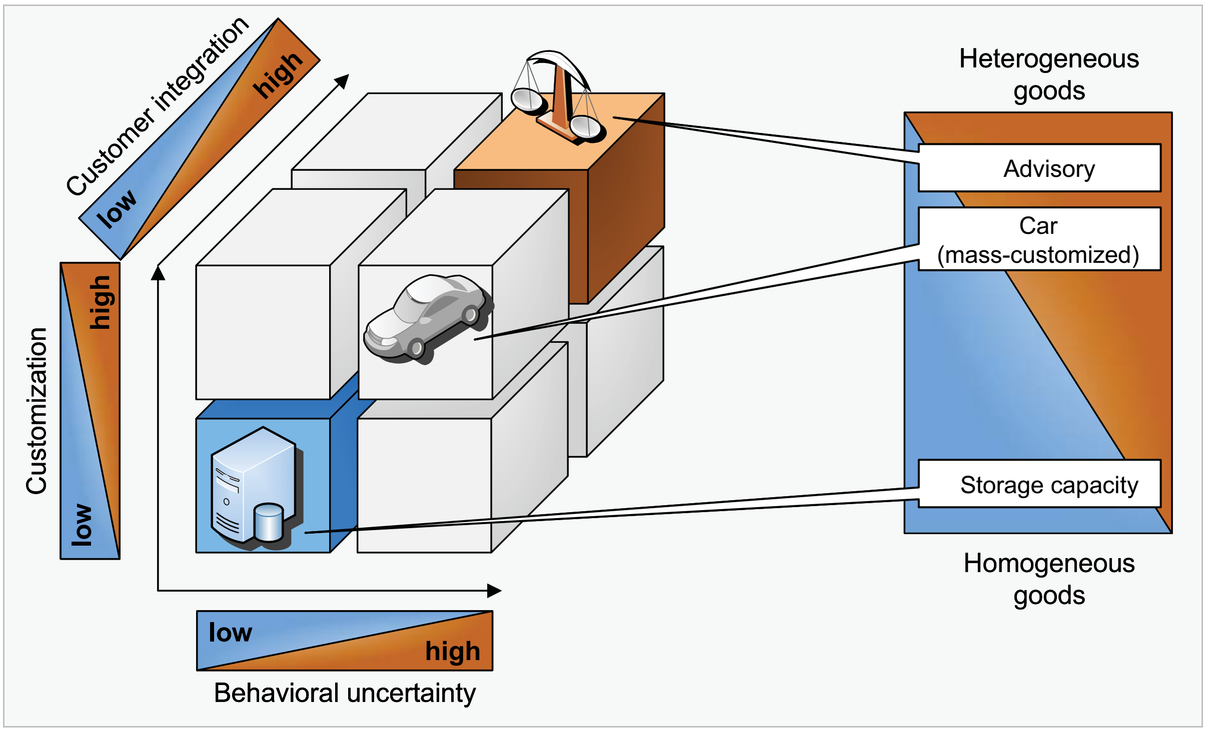

Figure 6: Typology of goods (based on [Wora96, 69])

The particular object of trade in the scenario of this work is *storage capacity* in units of one gigabyte per month (GB/month).

2.4.2 Price Formation Mechanisms

2.4.2.1 How Prices Emerge

The price demanded by producers represents the evaluation of a product in monetary units. From a customer's point of view, the price is a sacrifice made to benefit from the possession of something, i.e. his *willingness-to-pay* depends on his associated utility with the particular good [Simo92, 3–4]. From the producer's position, the price has to compensate for costs incurred in the manufacturing process and has to yield profit for the company [Simo92, 25], [Vari06, 386–387]. Thus, the goals of customers and producers are rivaling.

Furthermore, the market structure influences price formation as well: on competitive markets with numerous customers and producers (*polypolies*) prices emerge from aggregate demand and supply [Simo92, 20–27]. This equilibrium principle relates back to the findings of Leon Walras, but is disputed when constraints such as informational asymmetries persist [Vari06, 572], [McMc87, 700], [Aker70, 492].

Since utility is subject to individual preferences, customers' willingness-to-pay varies as well: producers are keen to match these price limits in order to maximize turnover. If the price is set too low, demand exceeds the production plan, and if the price is too high, customers are deterred and supply exceeds demand. In both cases social welfare is forgone. Thus, for complex bundles, market research is conducted to measure the utility perceived by consumers and to derive the associated willingness-to-pay. But the aggregation of individual estimates is often problematic and seldom reduces information asymmetry sufficiently [Meff05, 542–548].

Price formation mechanisms describe how prices come into existence on markets. Mechanisms can be grouped in *variable pricing*, *one-sided posted pricing* and *two-sided posted pricing* (Figure 7). In variable pricing, price and product details result from bargaining and negotiations between the respective parties. Since no formal rules are given, this mechanism is excluded in this work [WRSc05, 62]. Instead, we explain one-sided posted pricing and two-sided posted pricing.

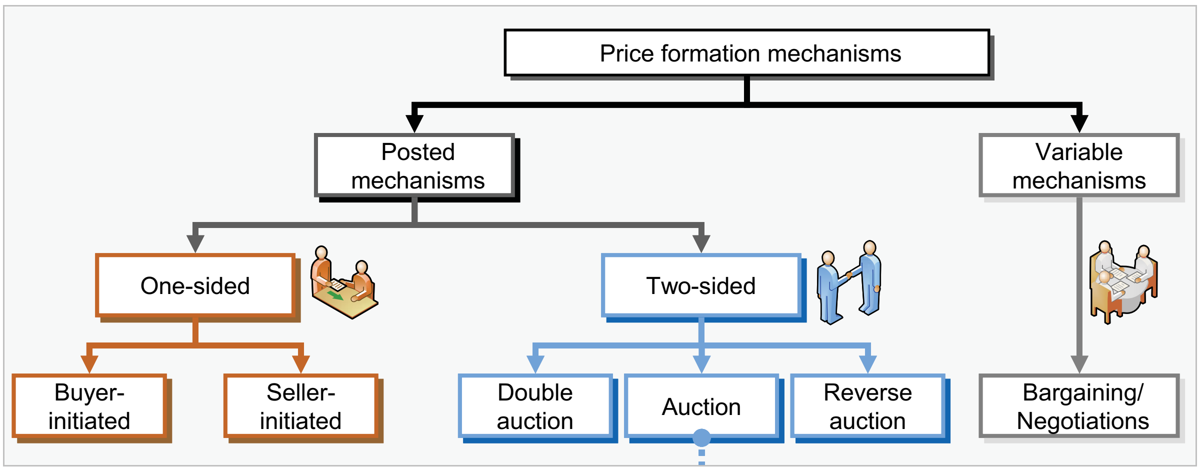

Figure 7: Price formation mechanisms [WRSc05, 62]

2.4.2.2 One-sided Posted Pricing

In one-sided posted pricing, either the seller or the buyer posts a fixed price and defines the characteristics of the product. Usually producers announce the price on the basis of incurred costs and market structure. Potential buyers then decide whether to accept or to reject the offer in conformance with their willingness-to-pay [WRSc05, 62–63]. This mechanism requires knowledge about the buyer's preference structure in order to exploit the full potential benefit from the bargain [Meff05, 542].

2.4.2.3 Two-sided Posted Pricing: Auctions

Two-sided posted pricing involves both seller and buyer when it comes to defining product price and characteristics. If the seller designs the product in question, the buyer announces his price – and vice versa. The according mechanism for this way of price determination is the *auction* in one of its forms [WRSc05, 63]. Quoting McAfee and McMillan, "an auction is a market institution with an explicit set of rules determining resource allocation and prices on the basis of bids from the market participants" [McMc87, 701]. The design of auctions, the pros and cons of specific bidding rules, and the resulting bidding strategies are the subject of *auction theory* [McMc87, 700], [MiWe82, 1090–1093].

Auction types can be categorized by the number of sides submitting bids (*auction*/ *double auction*) and by the market role of the *auctioneer* (buyer/ seller) (Figure 8). Auctions conducted by buyers are called *reverse* or *procurement auctions* [KaCa04, 15], and auctions in which both supplier and customer place bids are named *double auctions* [Klem04, 35].

The four fundamental auction forms are the *Dutch auction*, the *English auction*, the *first-price sealed-bid (*FPSB*) auction* and the *second-price sealed-bid auction* (also known as *Vickrey auction*). The Dutch auction (*descending-bid auction*) starts with a high price and decreases continuously until one bidder accepts the price and calls out. In the English auction (*ascending-bid auction*), the auctioneer commences with a low price and increments the price until one bidder remains (who wins the event). In FPSB and Vickrey auctions bidders cannot see their competitors' bids, and the object is won by the bidder who submits the highest bid. The difference lies in the final price: whereas in the FPSB auction, the winner has to pay his full bid, the winner in

Vickrey auctions pays the bid of the *second*-highest bidder [Klem04, 11–12].

On the basis of the *Revenue Equivalence Theorem,* we assume the seller's expected revenue is the same in all four fundamental auction forms (to be precise, revenue is equal *on average*). In this case the winner is the participant with the highest willingness-to-pay, induced by the individually perceived utility [Klem04, 17–18], [McMc87, 710–711].

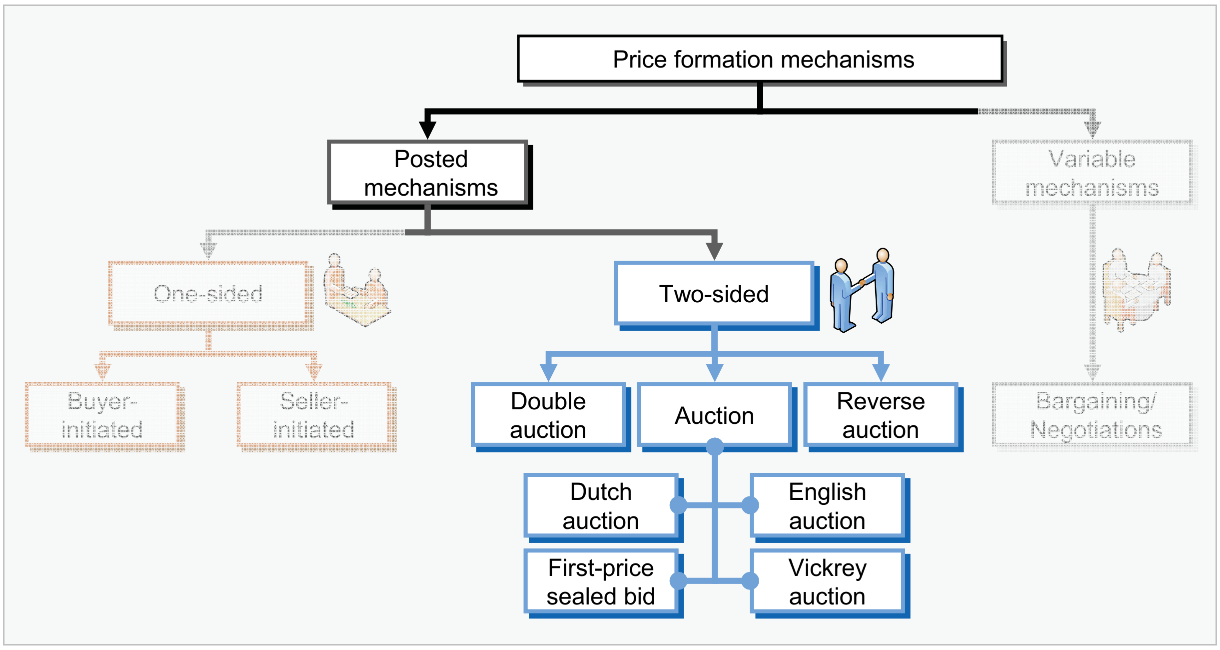

Figure 8: Well-known auction types (based [WRSc05, 64])

Allowing for informational asymmetries, markets are less competitive on the suppliers' side and rather constitute monopolistic situations [McMc87, 703]. This complies with our future scenario – every supplier and his offer are more or less unique and are requested by a group of interested buyers.

In a recent simulation in the eRep project the authors presumed a mechanism similar to the one implemented at the popular Internet auction platform *eBay* [BJTr08, 13]; we follow these developments and use an English auction to determine the price of the particular good.

2.5 Differentiation through Reputation

2.5.1 Reputation and Image

2.5.1.1 The Function of Reputation

In modern economies, companies build *reputation* to differentiate themselves from competitors and gain competitive advantage [Fomb96, 80]. A good reputation can stimulate product sales, increase the chance of hiring the best employees and attract potential investors [FoSh90, 233–234]. As an intangible asset, reputation is of paramount importance for service providers and can be shaped through various practices such as conducting *pro bono* activities or by company advertising campaigns [Fomb96, 112–136].

The peculiar importance for service providers can be explained as follows:

In comparison to commodities, services are, among other things, characterized by a high degree of uncertainty. As a result of asymmetrical information between service providers and customers, potential buyers face high risks of being exploited after signing a contract (*moral hazard*) [MeBr06, 97], [Wora96, 62]. Taking those risks into account, consumers' willingness-to-pay decreases and eventually leads to the destruction of markets for high-quality products [Aker70, 490–491].

Reputation is an effective panacea which indicates reliability and mitigates moral hazard [Wora98, 47]. Building a good record is expensive and time-consuming; and since reputation is sensitive to dishonesty, deceitfulness and fraudulence, a good name promotes self-commitment by encouraging the owner to continue fair business practices [MeBr06, 98]. In consequence, customers believe past behavior is a good predictor for future conduct [Roth01, 59]. This corresponds with Axelrod's "shadow of the future", a phenomenon describing why future interactions are constrained by behavior in the past [Axel88, 11].

2.5.1.2 Building Blocks of Reputation: Image and Social Reputation

The assessment of one partner's reputation depends not only on a common agreed social estimate. Instead, we distinguish between an individual's perception and the social opinion about an entity [BKOc04, 1588].

Through the evaluation of outcomes of past transactions individuals gain *impressions* and form an estimate of a partner: this is called *image*. Furthermore, the common belief about the image of a target spread in social communities is considered as an objective result of evaluations and complements the assessment of the target's reputation. This component is termed *social reputation* [Erep06, 7–8]. As reputation again stipulates trust, a cycle of reputation building is formed (Figure 9).

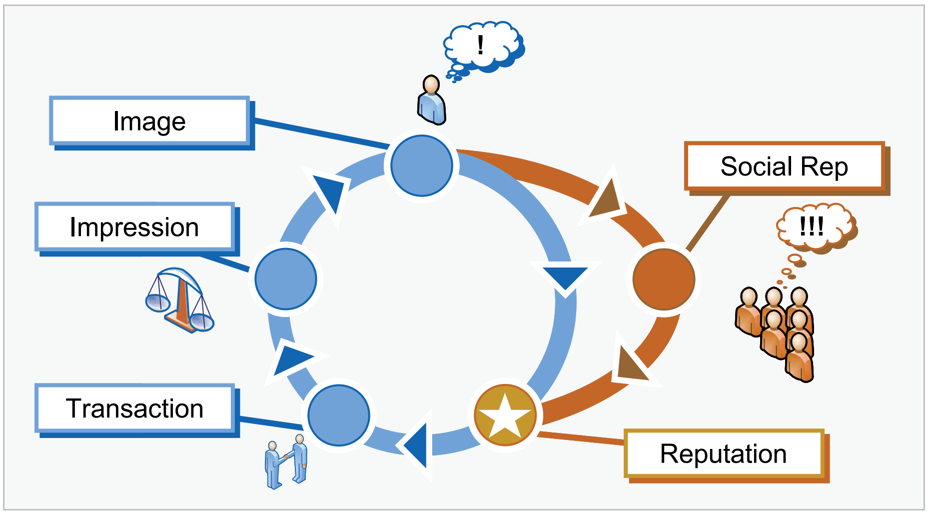

Figure 9: Building blocks of reputation

With respect for brevity, we omit a further explanation of reputation here; and for a deeper understanding in the context of the eRep project we refer to [CoPa07].

2.5.2 Reputation Systems

2.5.2.1 Reputation Systems and Feedback Mechanisms in ALN

A reputation system serves the purpose of providing information about the reputation of an individual: The system has to gather, extract and evaluate feedback from information and to assign it to the relevant entity [RZFK00, 46]. Results from experiments conducted in controlled environments emphasize the value of reputation systems and advocate their implementation; empirical studies support these findings [RZSL06, 26], [Ocke03, 310], [Kese02, 21], [ReZe01, 23].

The great importance of reputation in ALNs can be explained this way: Since an extremely large number of participants offer and demand services, repeated encounters are very unlikely. This in turn inhibits building images from impressions. Resnick and Zeckhauser support this assumption: In their study of empirical data from eBay they discovered that 89 percent of the examined bargains were conducted by a unique seller-buyer pairing. The authors draw the conclusion that eBay's reputation system rewards honest behavior, although the particular results of different studies on the system's effects vary in detail [ReZe01, 9].

To summarize, effective reputation systems foster the trade among strangers and "help people decide whom to trust, encourage trustworthy behavior, and deter participation by those who are unskilled or dishonest" [RZFK00, 46].

Feedback mechanisms in ALNs can be distinguished from word-of-mouth networks of human beings in terms of three aspects [Dell03, 1410]:

First, the large scale of participants in the system requires that the number of collected feedbacks exceeds a certain threshold before it makes a difference. No entity pays attention to the social reputation if the number of underlying appraisals is too low.

Second, information technology allows the detailed design of feedback mechanisms and the formulation of algorithms for transforming feedback into aggregated values. For example, eBay displays the arithmetic mean of the sum of positive feedbacks collected by each member. The number of positive feedbacks exceeding negative ones is summarized and a colored star next to the sum signals the awarded reputation [Ebay08a], [Ebay08b]. The application of logical evaluations induces transparency and comparability of reputation values.

Third, ALNs are virtual constructs and prevent personal encounters. Prior to transactions, individuals cannot interpret signals from the surroundings (*tangibles*) or empathize with the potential partner. The degree of uncertainty exceeds the one of typical service providers'. For example, when seeking advice from a lawyer, people pay attention to the decoration of the waiting room, the district in which the office is located or the brand of the suit the lawyer is wearing (cf. [MeBr06, 294], [Bitn03], [Wora01, 273]). In ALNs, the agent has no such signals, since company websites or digital business cards will be of little help.

In Internet marketplaces, reputation systems are realized through central institutions collecting and evaluating feedback information [Dell03, 1408]. This does not apply to the individual image of a participant except for its contribution to social reputation.

As intuitively assumed and supported by the findings of a lab experiment in 2004, the gain from one's own experience is likely to exceed a cumulative public reputation value [BKOc04, 1595]. These findings are underpinned by recent survey results showing 60 percent of private online shoppers remain loyal to vendors they had a positive shopping experience with [Niel08, 5].

Since the effects of locally managed reputation are investigated in the eRep project, the following paragraphs focus on such reputation systems.

2.5.2.2 A Panoramic View on Current Systems

It is beneficial for the development of an appropriate reputation framework to contrast outcomes from empirical research with theoretical findings [Dell03]. A valuable roundup of reputation systems serves three purposes: it lists existent frameworks, describes the designs, and extracts particular contributions from each system.

Sabater and Sierra provide such a summary: they reviewed thirteen different concepts and classified them on seven dimensions (cf. Appendix A 2, p. 106, and for the abbreviations Appendix A 1, p. 105) [SaSi05, 55–56]. We explain two of these dimensions, since they exert direct influence on the selection of decision-making tools.

First, *information sources* comprise the types of sources taken into account when determining the reputation value of another entity. The perceived reputation of a trader depends on the subjective image of the customer built from impressions and the trader's circulating social reputation. The subjective impressions stem from experiences made in direct interactions or observations with the trader. Following the narrow definition above, witnesses' experiences are aggregated and result in social reputation. Beyond these experiences, information based on the trader's societal affiliations and social relations is likely to influence his picture. Hence, those potential sources are as well subsumed under social reputation [SaSi05, 35–37].

Second, an associated *reliability measure* helps to understand how stable each impression is. Thus, our customer can use the measure to weight the information value. In communities with a tremendous number of entities, the reliability measure serves as a threshold and filters less credible impressions. But even the subjective image a customer has is instable: Memories are fugacious, and in the course of time experiences blur or disappear completely. By assigning a reliability measure to each impression, the individual computation of an aggregate reputation score becomes more precise and comprehensible [SaSi05, 40–41].

Our scenario with autonomous and deliberate agents encourages local decision-making. Hence, a reputation system that makes use of direct experience as well as witness information has to be implemented. Though not critical, a measure for reliability is useful when dealing with large-scale MAS. With the aid of Sabater and Sierra's comparison, two possible systems are identified: *AFRAS* and *ReGreT*.

Since ReGreT includes a comprehensive framework for evaluating sociological information, we prefer it to AFRAS and present it in the following chapter.

2.5.2.3 ReGreT

The ReGreT system consists of a direct trust and a reputation module to assess the trustworthiness (*trust*) of a prospective, so called *target agent*. Trust towards a target agent is the weighted sum of *social reputation* and *direct trust* (i.e. *image*). The computation of each component is determined by the system's architecture: it distinguishes between three reputation dimensions, the *individual dimension*, the *social dimension* and the *ontological dimension* (Figure 2 1) [SaSi01, 194].

In the next paragraphs, each dimension with its components will be presented in a nutshell; for a detailed explication see [Saba03, 44–62].

On the individual level, outcomes of dialogues between agents are used to compute a *direct trust* value. An outcome is represented by a subjective rating and a tuple of information; it is stored in the *outcomes database* (ODB). The tuple of information characterizes the outcome (e.g. price or expected quality) and the rating reflects the perceived evaluation. Direct trust is usually the most stable source to predict the sincereness of a partner; on the downside, it is unavailable for new entrants and expensive to build [Saba03, 44–46].

In the social dimension, the reputation measure is computed by the weighted results of three sources: *witness*, *neighborhood*, and *system reputation*. The weights are obtained from the credibility of each source, which is in turn calculated from the numbers of impressions and the standard deviations [SaSi01, 195].

We talk about *witness reputation* when information is collected from other agents who transmit their direct experiences or feedback obtained from peers. Evaluated impressions of witnessed outcomes are recorded in a second storage, the *impression database* (IDB). *Neighborhood reputation* is determined by the target's social environment and the relations the target has established with his environment. It is comparable to prejudice, but not necessarily discriminating. *System reputation* is based on the target's role in a group. It assumes that roles adhere to certain observable features or behaviors which may be assigned to the target agent [Saba03, 47–48].

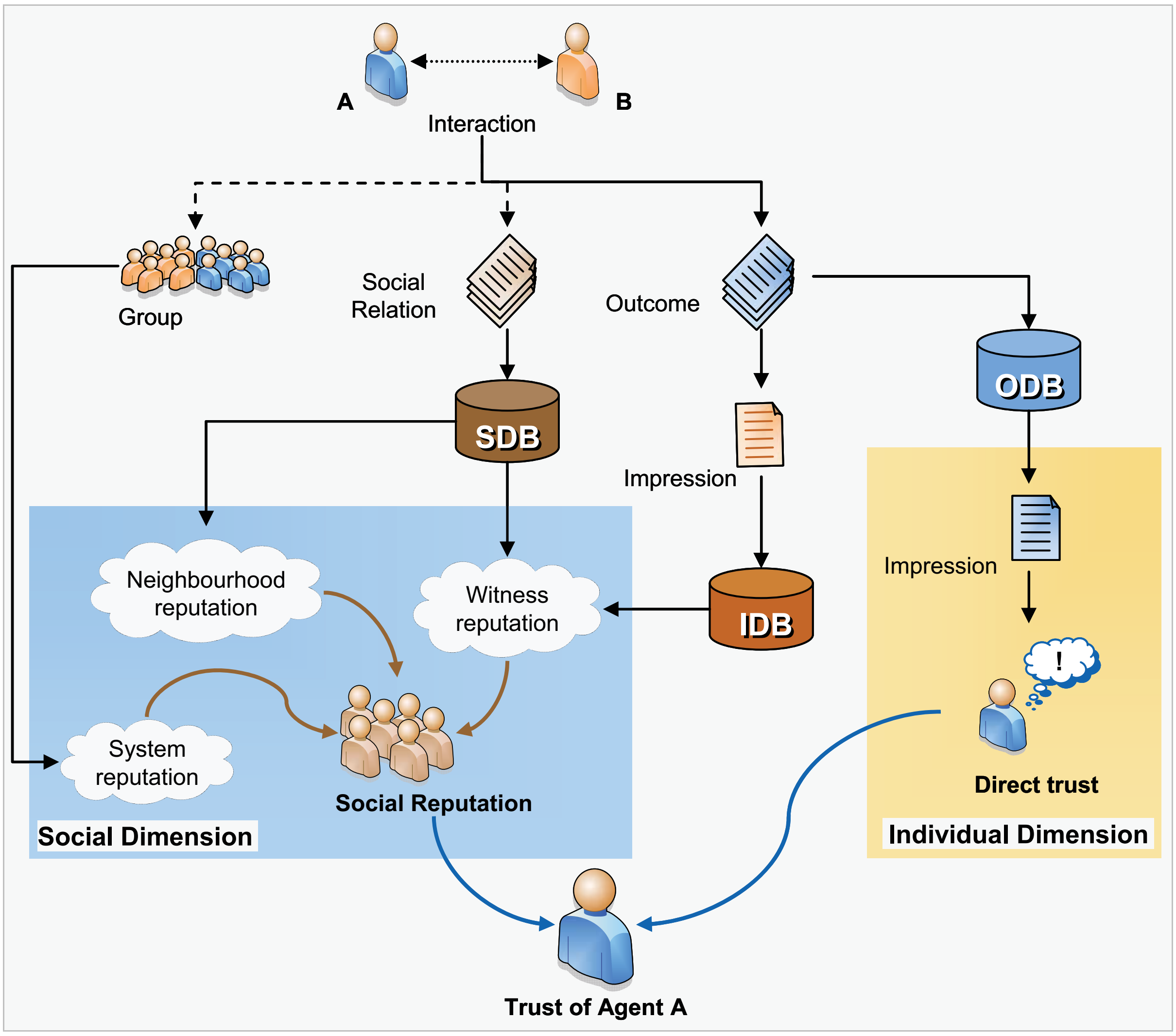

Figure 10: Calculation of trust in ReGreT (based on [Saba03, 92])

The computation of neighborhood and system reputation depends on the group the individual belongs to; thus, both can be understood as group knowledge, and both are influenced by the social structures. Those structures, mapped as *sociograms*, are stored in a third container, the *sociogram database* (SDB). Though not fully specified yet, sociograms will support each estimate of credibility for all considered impressions by providing aid for proper weight assessment (e.g. witness reputation issued by a node related to the target agent may be biased and thus less valuable than others' feedback) [Saba03, 51], [Saba03, 41].

Finally, the ontological dimension describes the context of information on which the target agent is rated. The ODB does not merely provide an aggregated value on each outcome but also detailed information on attributes such as price or delivery date; our subject can evaluate the overall impression by combining different aspects according to his preferential structure. This reflects different perceptions in real life, in which the seller's reputation strongly depends on the rating customer [Saba03, 61].

König et al. propose a completely decentralized implementation of the ReGreT system using peer-to-peer technology for information exchange [KKWi07]. Due to its complexity, we reject their suggestion and presume the IDB is centrally implemented and social reputation of an agent is identically perceived by all participants. Of course, this does not affect the decentrally calculated *image* estimate.

We assume our participants will consider potential partners' social reputation as well as direct trust from previous encounters. Consequently, social reputation and image are *differentiating features* for agents in MAS.

2.6 Decision Making

2.6.1 Theory of Decision

Decision theory is concerned with a *decision-maker's* (DM) goal-directed rational behavior of coming to a decision in presence of possible options. *Rationality* implies deliberating about the action before and during decision-making, as well as commitment to the selection [SzWi74, 3–5]. In this work agents undertake decision-making and serve as proxies for their principal, the DM.

A distinction is made between normative and descriptive decision theory: Normative decision theory prescribes how problems can be solved. It provides advice on problem solving by formal means of depicting initial situations and solutions. In contrast, descriptive decision theory researches empirical findings and deals with the *ex post* analysis of decisions made [Laux07, 2], [SzWi74, 18–21].

Decision-making is a multi-stage process that "begins with the identification of a stimulus for action and ends with a specific commitment to action" [MRTh76, 246].

The famous economist and Nobel prize winner Herbert A. Simon (1960) proposed a *sequential* model with the three principal phases *intelligence*, *design*, and *choice* – similar in structure and content to the models later developed by Irle (1971) or Szyperski (1974) (Figure 11) [Simo77, 40], [SzWi74, 7–10].

The first phase, *intelligence*, covers the search for decision predicates in the environment; Simon has baptized this phase in analogy to the military meaning. The following step, *design*, involves forging, developing, and studying possible conduct. Finally, the *choice* activity deals with selecting a particular conduct from the available ones [Simo77, 40–41].

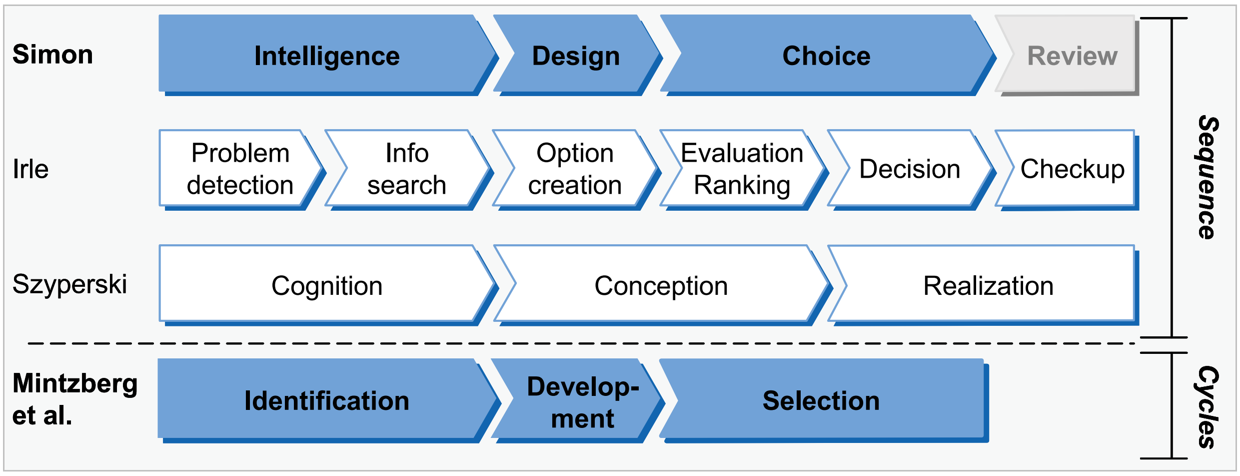

Figure 11: Decision-making process (cf. [SzWi74, 7–10], [Simo77, 40–41])

Later on, Mintzberg et al. (1976) recommend a *non*-sequential, *iterative* model with three intertwined phases comprising of seven central *routines* (Figure 12) [MRTh76, 252]. In contrast to the sequential models, their proposal assumes rather an iterative process of routines than the linear succession of actions. Iterations include cycles between routines *within* a phase as well as cycles between phases.

The initial phase is termed *identification* and comprises two routines. The first, *decision recognition*, is concerned with the identification of problems, crises, and opportunities. The second routine, *diagnosis*, deals with accumulation and assessment of related information, and determination of cause-effect relationships [MRTh76, 253–254].

The *development* stage is composed of the *search* and the *design* routine. While the *search* aims at finding existing solutions, *design* is about the development of custom-made solutions as well as the modification of ready-made ones. The purpose of both routines is defining options for later decision [MRTh76, 255–256].

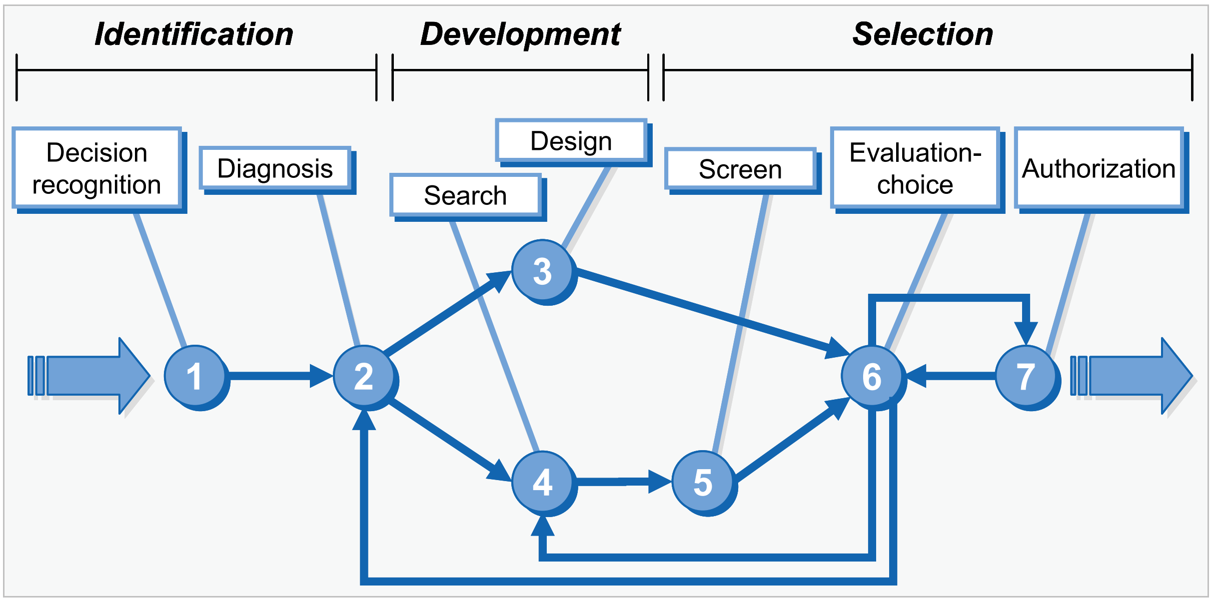

Figure 12: Non-sequential decision-making process [MRTh76, 266]

Finally, during the *selection* stage, three routines take place: The *screen* routine is concerned with the elimination of infeasible alternatives. In the *evaluation-choice* routine possible courses of action are evaluated and a choice is made. The last routine, *authorization*, deals with the submission of the decision to superior instances for approval [MRTh76, 257–260].

Depending on the model, the focus for this work lies on the choice stage (Figure 11) or the selection stage (Figure 12), both dealing with formal models for comparing and ranking considered alternatives.

2.6.2 The Classical Model for Decision Making

Whether we approve of Simon's sequential decision process or the cycling phases of Mintzberg et al., decision-making is concerned with selecting one or more options from a number of alternatives. In order to support DMs, *decision matrices* are commonly used to visualize and formulate decision situations [Laux07, 36–37], [YoHw95, 3]: The columns in the matrix represent the *criteria* and the rows the *alternatives* with their specific *outcome* vector.

We show an example situation below: A passenger who is requested to journey low-budget from Frankfurt to Munich is confronted with three travel options (Table 3).

Table 3: Example of a decision matrix

Alternative \ **Criterion**	C_1: Costs incurred
A_1: Take the train	EUR 70
A_2: Take the car	EUR 120
A_3: Travel by airplane	EUR 150

A decision matrix is constructed by gathering and attributing information to alternatives and criteria (Figure 13; processes in this work are illustrated using *activity diagrams* of the *UML* notation, see [OMG08]).

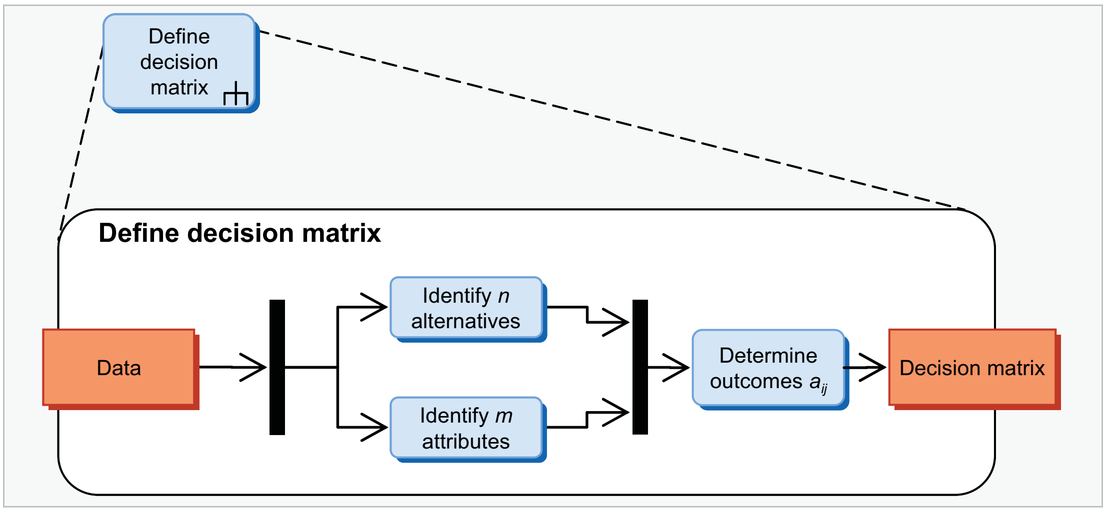

Figure 13: Subprocess of defining a decision matrix

A decision matrix is a particular decision *model* with some building blocks which are always apparent (Table 4) [Laux07, 19–26]. We denote by the decision matrix $\mathbf{A}$ on the whole $\mathbb{R}^{n \times m}$, the set of n alternatives $A = A_i,\ i \in \{1,\ldots,n\}$, the set of m criteria $C = C_j,\ j \in \{1,\ldots,m\}$. Upon deciding, our passenger picks A_1 and faces the safe outcome a_{11}= 70, i.e. paying 70 Euros for the train ticket.

Table 4: Terminology in decision-making [Laux07, 19–26]

Term	Description	Symbol	Example
Goal	A goal describes an **aspired** situation or change of present state. It is formulated using a *preference function* and the criterion to optimize.		Travel *cheaply* from Frankfurt to Munich (one-way)
	The *preference function* (which represents the DM's **preference structure**) evaluates outcomes.	$\Phi = \Phi(A_i)$	
Alternative	An alternative is a **unique** option characterized by a specific outcome. At least two alternatives are necessary to require decision-making.	A_i	A_1: Take the train A_2: Take the car A_3: Travel by airplane
Outcome	An outcome is a vector of values representing a **unique combination** of goal-relevant *criteria* of an alternative. The vector has to be unique to distinguish his respective alternative from others.	a_{ij}	a_{1j}: (Costs: EUR 70) a_{2j}: (Costs: EUR 120) a_{3j}: (Costs: EUR 150)
Criteria	Criteria are **parameter values** for goals (e.g. costs, duration).	C_j	C_1: Cost C_2: Duration
State (environmental)	Environmental states depend on **exogenous parameters** which influence decision-making. A state consists of influencers, i.e. data that changes the parameter values of outcomes and thereby the evaluation of alternatives. States can either be uncertain or definite; whereas the latter simplifies decision-making (values of outcomes are scalar and no inherent vectors), uncertainty involves risk estimation.		Instable gas price, new *outcome vector* for alternative two: a_{2j}*(low gas price)*: (Costs: EUR 95) a_{2j} *(normal gas price)*: (Costs: EUR 120) a_{2j} *(high gas price)*: (Costs: EUR 140)

The relationship between these building blocks in the classical model of decision-making is depicted below (Figure 14): We see the outcome depends on the interplay of decision and current state.

With respect to brevity, we disregard uncertainty and environmental states here. This in turn leads to the following simplification:

$$\left(\Phi(A_i) \equiv \Phi(a_i)\right) \wedge \left(u(a_i) \equiv u(A_i)\right) \Leftrightarrow \Phi(A_i) = u(A_i)$$

The calculated preference value Φ of an alternative A_i is equal to the utility u_i of the outcome a_i [Laux07, 27].

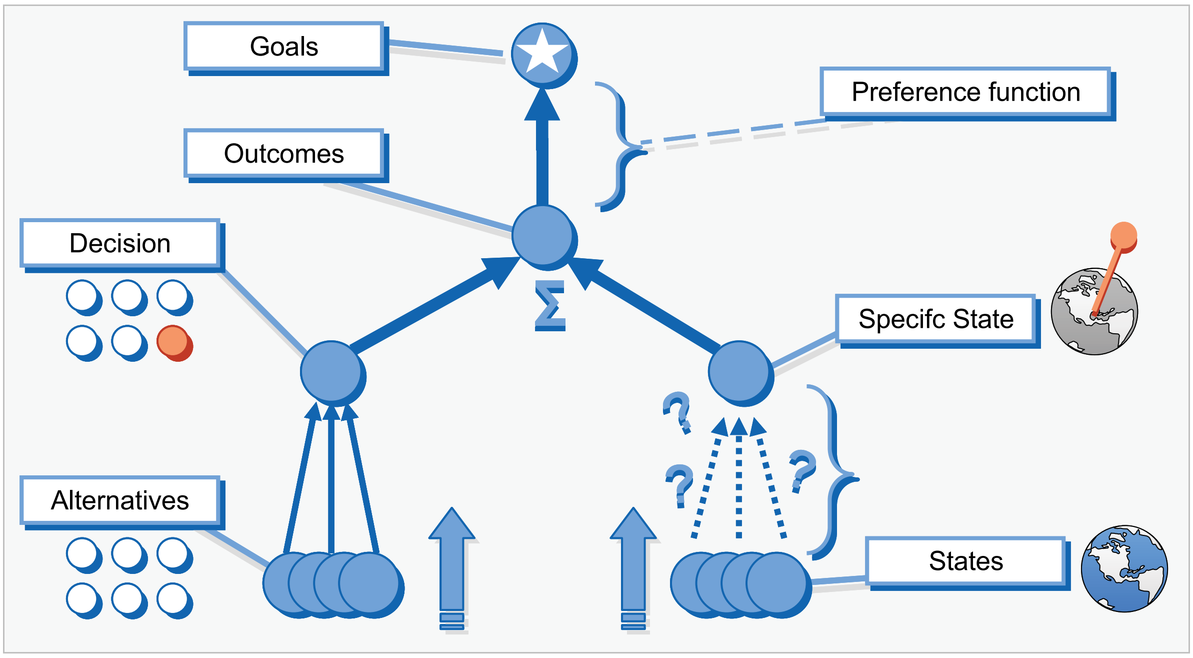

Figure 14: Classical model of decision-making (based on [ZiGu91, 3])

Thus, when we know the preference value for all alternatives, an utility-maximizing decision can be made without explicitly deriving utility from each parameter value. The question is whether all alternatives with their respective outcomes are available or not. Returning to the example (cf. Table 3), we recommend taking the train, which dominates the other alternatives in minimizing costs.

2.6.3 Multiple Criteria Decision Making

Under certainty, classical models can cope with decision-making as long as the preference function draws a comparable value out of each alternative. Everyday problems are usually more demanding: A comprehensive judgment involves balancing multiple goal-related criteria which are often competing [BeSt02, 1]. This challenge is called *aggregation problem* [Roy05, 14]. The modified decision matrix (Table 5) from the previous Subsection adds the criterion “travel time” to the problem.

Table 5: Example of a multiple criteria decision problem

	Criteria	
Alternative	x_1: Costs incurred	x_2: Travel time
A_1: Take the train	EUR 70	4 hrs.
A_2: Take the car	EUR 120	3.5 hrs.
A_3: Travel by airplane	EUR 150	2.5 hrs.

Although this problem seems simple, the challenge lies in managing the trade-off between travel time and costs (assuming less travel time is associated with a higher utility). Time and costs are *incommensurable* units (What is the value of an hour in Euros? How much time can I buy for a certain amount of money?) and no alternative dominates the others on both dimension (the train is now less attractive due to the long travel time). We are concerned with *Multiple Criteria Decision Making* (MCDM) when we take account of multiple conflicting criteria which need to be balanced [BeSt02, 5].

In our later scenario, the buying agent is choosing between several sellers, which differ in social reputation, image and the demanded price. While shoppers seek concurrently a high reputation and a low price, well-reputed sellers will likely seize their good name and ask for a premium (cf. the results of the experiment in [RZSL06, 21]).

2.6.4 Preference Modeling through Utility and Values

The predictability of the environmental states influences the means of preference modeling and distinguishes between preference representations under *certainty* and under *risk*. When we deal with uncertainty or risk, we refer to a preference representation function as a *utility function*, and when all states are certain, we refer to a preference representation function as a *value function* [Dyer05, 267–268], [BeSt02, 95], [KeRa93, 15–16].

In sympathy with Dyer et al. we exclude the field of *Multiattribute Utility Theory* here and assume value functions are either implicit or no such function exists at all [DFS+92, 647]. And since we also omitted cases of uncertainty and risk, we do not need to pay attention to utility functions from now on (for details on utility see [Vari06, 54–56]). Instead, we define *value* as being proportional to utility, i.e. a higher value implies always a higher utility (i.e. *monotonically increasing*).

In case outcome and evaluation are positively correlated, we deal with a *benefit attribute* (i.e. *maximization* goal), in case they correlate negatively, a *cost attribute* is considered (i.e. *minimization* goal) [YoHw95, 15].

At this point, we denote the dependency of the value v_{ij} of an attribute's outcome a_{ij} as a value function $v_{ij} = f\left(a_{ij}\right)$, or $v\left(a_{ij}\right)$ (techniques for the attribute-wise rating of outcomes are presented in Subsection 3.2.2). We assume furthermore the following two axioms among the preferences are satisfied, which are formulated for the case of benefit attributes [1] [Vari06, 35], [Laux07, 31–32]:

1. *Completeness*: Any couple of alternatives A_α, A_β and their outcomes $a_{\alpha j}$, $a_{\beta j}$ in a set of n alternatives can be compared and valued, so that $a_{\alpha 1} \succeq a_{\beta 1} \Leftrightarrow v_{\alpha 1} \succeq v_{\beta 1}$ for $\forall \alpha, \beta \in \{1, \ldots, n\}$. [2]
2. *Transitivity*: Comparing and valuating three alternatives $A_\alpha, A_\beta, A_\gamma$ ($v_\alpha, v_\beta, v_\gamma$) the following has to hold good:
    a. If outcome a_α is preferred to or equal to the outcome a_β and the outcome a_β is preferred to or equal to the outcome a_γ, then a_α is preferred to or equal to a_γ. Formal: $(a_\alpha \succeq a_\beta) \wedge (a_\beta \succeq a_\gamma) \rightarrow (a_\alpha \succeq a_\gamma)$
    b. If outcome a_α is equal to the outcome a_β and the outcome a_β is equal to the outcome a_γ, then the outcome a_α is equal to the outcome a_γ. Formal: $(a_\alpha \sim a_\beta) \wedge (a_\beta \sim a_\gamma) \rightarrow (a_\alpha \sim a_\gamma)$.

The two axioms seem sound but are not unquestionable: especially transitivity is problematic, because human beings can hardly distinguish between complex options. In the light of procedural rationality, the ability of individuals to conduct rational behavior is determined by cognitive powers and limitations (*bounded rationality*) [Simo78, 67], [SzWi74, 29–31].

In our scenario, we assume our agents are capable of taking *all* aspects into account and their time to process information is sufficient, thus they do not suffer from an excessive supply of information (*information overload*) [FaDr02, 127].

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1 For cost attributes, the binary relations between two outcomes are inverse to the relations of their values.

2 In case of $\alpha = \beta$ the axiom of reflexivity is satisfied.

3 Multiple Criteria Decision Making

3.1 Classification of MCDM Methods

A wide collection of approaches is available to support individuals or groups in decision-making but none outperforms all other methods. The selection of an appropriate method depends on the environment and is influenced by several factors such as available information, desired type of outcome or number of alternatives [BMP+00, 150], [Tria00, xxvi]. In order to provide an overview of available MCDM methods, it is helpful to classify these methods. Beforehand, we summarize some general aspects of data measurement and introduce scale normalization and weighting methods.

First of all, MCDM methods can be grouped according to the certainty of information: data may be either *deterministic*, *stochastic* or *fuzzy*[3]. This work focuses on deterministic cases, for approaches covering uncertainty see [Stew05] and for fuzzy MCDM methods see [GrLa05], [ZiGu91, 247–266].

Further, MCDM can be separated into *Multiple Attribute Decision Making* (*MADM*), *Multiple Objective Decision Making* (*MODM*) and *Decision Aids* (Figure 15) [ZiGu91, 25–28].

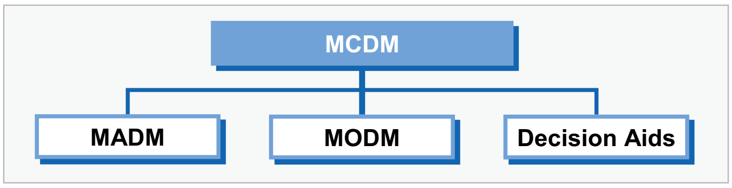

Figure 15: MCDM methodology

MADM concentrates on situations with a predetermined set of alternatives, i.e. the *selection* of an alternative from a *discrete* decision space. In contrast to MADM, MODM covers problems in which alternatives are not explicitly defined *a priori*. However, constraints and objectives are given to *design* efficient solutions from the *continuous* decision space (these cases are often termed *vector-maximum* problems) [Tria00, 1], [ZiGu91, 25], [HwYo81, 2–4]. Following this classification, we present a

3 “Fuzzy” refers to information which is not represented by an exact value, but instead is subject to a membership function that assigns values on a gradual base (see [Zade65]).

MADM methodology and a classic MODM approach. Apart from MADM and MODM, *Decision Aids* facilitate decision-making and not necessarily produce an unambiguous solution. We briefly introduce the approved outranking technique along with a corresponding method; outranking approaches estimate efficient solutions on the grounds of *pairwise comparing* alternatives. [BeSt02, 233–234], [ZiGu91, 26–29].

The structure of this Section is as follows (Figure 16): We commence with a general introduction of different data types and weighting methods and their influence on decision-making (Subsection 3.2). Then we turn to MADM (Subsection 3.3) and explain a MODM method (Subsection 3.4). The last Subsection (3.5) is concerned with Decision Aids.

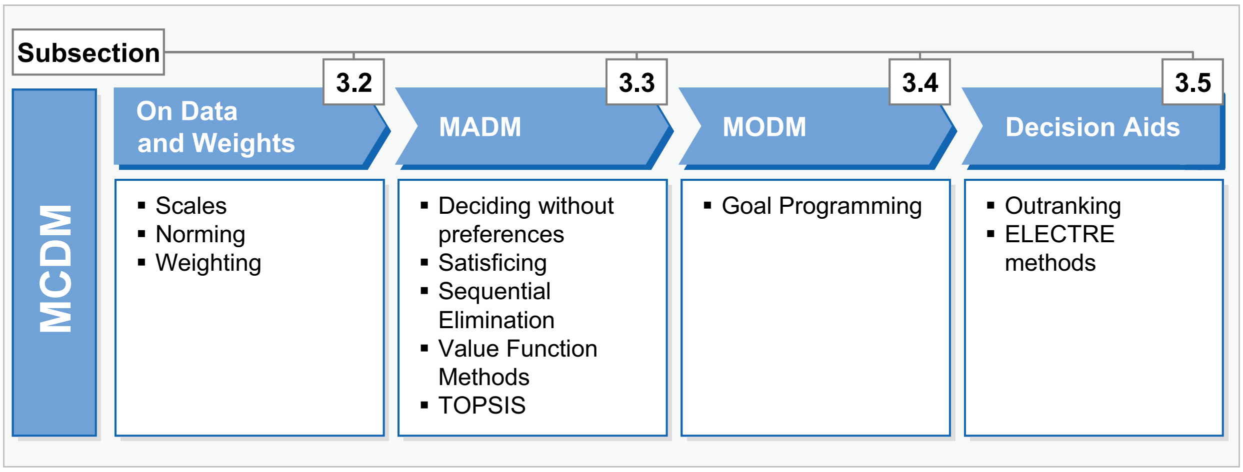

Figure 16: Outline of the 3rd Section

In order to facilitate the understanding, we provide an exemplary decision problem to illustrate the results for each method. This case study can be found in Appendix B.

3.2 On Data and Weights

3.2.1 Scales of Data

The information on a criterion, i.e. the *raw data* of the outcome, can be expressed in terms of numbers or characters which are subject to a specific *scale*. *Levels of measurement* distinguish between *nominal, ordinal* (grouped as *categorical* scales)*, interval* and *ratio* scales (comprised as *continuous, metric* or *cardinal* scales) [BEPW06, 4]. The scale levels and their distinct properties are sorted according to the number of mathematical operations and listed together with an example in concentration with a car purchase decision [Webe93, 10].

Table 6: Scale levels and their properties [BEPW06, 4–6], [Webe93, 10]

Scale	**Level of measure-ment**	**Properties**	**Mathematical operations**				**Specific measure**	**Examples**
			a)	**b)**	**c)**	**d)**		
Categori-cal scale	**Nominal**	Classification of qualitative values	Yes	No	No	No	Mode	Paint; Rims; Upholstery
	Ordinal	Rank order values, the difference between values is unknown	Yes	Yes	No	No	Median; quantile	Number of doors; Euro NCAP safety rating (five, four, ..., zero stars)[1]
Metric scale (cardinal)	**Interval**	Rank orders with constant difference between values but with arbitrary zero value	Yes	Yes	Yes	No	Arithmetic mean; standard deviation	Production date
	Ratio	Intervals between values can be measured and a non-arbitrary zero value exists	Yes	Yes	Yes	Yes	Geometric mean; coefficient of variation	Car price; trunk volume; gas consumption

a)	Equality ($=$) / inequality ($\neq$)
b)	Preference operations ($\succ$, $\prec$, $\sim$)
c)	Subtraction ($-$) and Addition ($+$)
d)	Multiplication ($\times$) / Division ($\div$)

[1] For details see [Euro04, 20–21]

It is of utmost importance that transformations from higher scale levels to lower ones are *always* possible [BEPW06, 6]: Though this will always include a loss of information (i.e. a decrease of entropy), it may be convenient or even necessary in the conduct of model building, e.g. suppose we were asked for the current weather and only ordinal information is demanded, we "transform" the precise, interval-scaled temperature of 25 degrees Celsius in a nominal value and answer with "it is warm". In contrast, upward transformations always include assumptions and leave space for interpretation (regarding the example, the questioner will hardly deduct the 25 degrees Celsius from the given answer). Thus, they have to be treated with caution. The uncertainty associated with transforming scales can be expressed in a *conversion measure* which illustrates the loss of precision [SPV+07, 32–33].

The selection of an appropriate scale and the translation of verbally expressed preferences into values are just two complex side-issues in decision-making; a discussion of various linear and exponential scale levels can be found in [Tria00, 50–55]. Because MCDM methods usually presuppose that data is provided in a sufficient format, we list this requirement in the comparison of MCDM methods.

3.2.2 Normalization Techniques for Equalizing Diverse Scales

The criteria in a given problem are usually measured not only on different scales but also in different units. Since this leads to problems in synthesizing criteria, compensatory MCDM methods demand comparable scaled data to model the overall preference [Roy05, 15]. We seek to assign a ratio scaled value $v = v(a)$ for each outcome by using a bijective value function so that the transformation does not affect the preference relation between two different outcomes [BeSt02, 85], that means

$$v(a_k) \succ v(a_l) \Leftrightarrow a_k \succ a_l \ \forall a \in \{a_{ij} | k \neq l\}.$$

Normalization techniques align raw data criteria-wise with regard to the intra-dimensional values of each criterion. We explain the *linear scale transformation* and the *vector normalization* below; other techniques are recorded in [TaJo97, 32].

Before normalizing, we need to consider how each criterion contributes to the overall utility. Normalization techniques treat benefit attributes differently than cost attributes. The *linear scale transformation* computes the normalized values v_{ij} dividing the surplus of outcome a_{ij} and the worst alternative by the range between maximum and minimum outcome (Table 7). The method considers the upper and lower bounds during normalization and thanks to the linear character of the function, ratios and intervals between outcomes remain unaltered [BMP+00, 102–103], [ZiGu91, 38–40].

Table 7: Normalization with linear scale transformation [BMP+00, 103], [ZiGu91, 39–40]

	Transformation function	**Domain**	**Precondition**
Benefit attributes	$v_{ij} = \dfrac{a_{ij} - a_j^{\min}}{a_j^{\max} - a_j^{\min}}$	$v_{ij} \in [0;1]$	For $\mathbf{A} \in \mathbb{R}^{n \times m}$ with $i = \{1,\dots,n\}$; $j = \{1,\dots,m\}$ and $a_j^{\max} = \max\limits_{\substack{i \\ 1 \le i \le n}}(a_{ij})$; $a_j^{\min} = \min\limits_{\substack{i \\ 1 \le i \le n}}(a_{ij})$
Cost attributes	$v_{ij} = \dfrac{a_j^{\max} - a_{ij}}{a_j^{\max} - a_j^{\min}}$	$v_{ij} \in [0;1]$	

The other technique, *vector normalization*, divides the outcome by the Euclidean norm of the respective criterion vector to retrieve a normalized value v_{ij} (Table 8).

Table 8: Vector normalization [YoHw95, 16], [ZiGu91, 38]

	Transformation function	Domain	Precondition
Benefit attributes	$v_{ij} = \frac{a_{ij}}{\sqrt{\sum_{k=1}^{n} \left(a_{kj}\right)^2}}$	$v_{ij} \in [0;1]$	For $\mathbf{A} \in \mathbb{R}^{n \times m}$ with $i = \{1,\ldots,n\}$; $j = \{1,\ldots,m\}$.
Cost attributes	$v_{ij} = \frac{\left(a_{ij}\right)^{-1}}{\sqrt{\sum_{k=1}^{n} \left(a_{kj}\right)^{-2}}}$	$v_{ij} \in [0;1]$	

After transformation, all criterion vectors lose their dimensions and attain the following uniform distance [YoHw95, 16], [ZiGu91, 38]:

$$\sqrt{\sum_{k=1}^{m} \left(a_{ij}\right)^2} = 1$$

Some authors skip the separate normalization step and directly model a *scaling constant* in the value function, but this does not affect the later results [Dyer05, 286].

In this work, we will explicitly state the normalization step and if nothing else is mentioned, we prefer the *linear scale transformation* to the *vector normalization*.

3.2.3 Weights as Means for Relative Importance of Criteria

Many MCDM methods ask for means to indicate the relative contribution of criteria to the DM's overall evaluation of alternatives. Weights reflect this relevance "in the sense of being a measure of the gain associated with replacing the worst outcome by the best outcome for this criterion" [BeSt02, 86].

This trade-off assumption between the criteria can be assessed using various methods of which we outline two ideas: retrieving weights from ranks and deriving weights from ratios between criteria.

The first group of techniques obtains *weights from ranks* [EdNe90, 53–54]. We need to list m criteria in a descending order, beginning with the most important and ending with the least important one. Practical means to construct the order are the $m \times (m-1) \div 2$ pairwise comparisons of criteria: The DM is asked for his judgment on the comparison of two criteria and responds with "preferred" or "not preferred".

We derive the value of the assigned weight w_j from the frequency the *j*-th criterion is preferred.

This method is all but unambiguous because the application of weight calculation formulas usually results in different, *inconsistent* values [YoHw95, 12–13]. We denote the *criteria comparison matrix*

$$\mathbf{C} \in \mathbb{R}^{m \times m}, \mathbf{C} = \left(c_{ij}\right)_{\substack{i=\{1,\ldots,m\}, \\ j=\{1,\ldots,m\}}}$$

with the c_{ij} as the relative importance of the *j*-th criterion towards the *i*-th one. Then inconsistency refers to preference statements which are intransitive and for which the *consistency condition*

$$c_{ij} = c_{ik} \cdot c_{kj} \ \forall \ \text{i,j,k} \in \{1,\ldots,m\} \qquad \text{with } c_{ij} = w_i \cdot w_j^{-1} \ \forall \ \text{i,j} \in \{1,\ldots,m\}$$

does not hold [ZiGu91, 54–55], [YoHw95, 13]. For this reason we withdraw this approach and turn to the second one, a group of techniques called *ratio weighting*.

These methods make use of *ratios* to display the trade-off between two attributes [Tria00, 57]. To be precise, we run again $m \times (m-1) \div 2$ pairwise comparisons of criteria, but in contrast to former techniques, we request ratio values from the DM which represent the preference ratio c_{ij} of one criterion over another, i.e. how many times is criterion *i* more important than criterion *j* [Tria00, 58–59]. As consistency implies reciprocity, we know that $c_{ij} = c_{ji}^{-1} \ \forall \ i,j \in \{1,\ldots,m\}$.

We denote the weight vector $\mathbf{w} = \begin{pmatrix} w_1 & \ldots & w_m \end{pmatrix}^T \in \mathbb{R}^m$ with $w_j > 0 \ \forall \ j \in \{1,\ldots,m\}$ and define normalized weights, so that $\sum_{j=1}^{m} w_j = 1$. Then, weights are computed as follows [ZiGu91, 55–56]:

$$w_j = \frac{\sum_{j=1}^{m} c_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{m} c_{ij}} \ \forall \ i,j \in \{1,\ldots,m\}$$

To assure consistency, the DM can either repeat the pairwise assessments and adjust the values or accept a certain error measure [EdNe90, 56–58]. `

Sophisticated techniques like Saaty's *eigenvalue approach* or the modified *least* *square approach* minimize this error value while determining optimal weights [BeSt02, 154–156], [Tria00, 57–60], [Saat80, 51].

When problems and criteria are complex, *value trees* facilitate defining criteria and assigning weights (Figure 17). Value trees make use of the hierarchical relation between criteria: Either an overall objective is decomposed *top-down* into several subordinate levels with families of criteria and child criteria, or inversely, criteria are composed to derive the paramount objective *bottom-up*. Then the DM compares each criterion with its siblings, and for each level comparison matrices are constructed and *relative weights* are derived [BeSt02, 140], [EdNe90, 62].

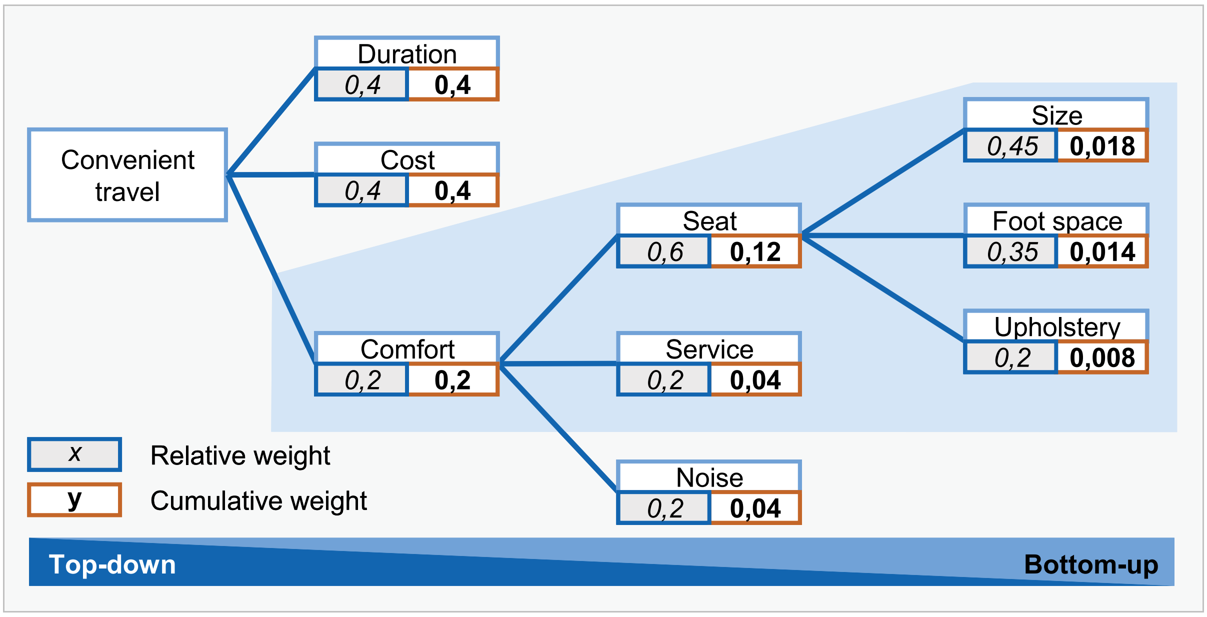

Figure 17: Relative and cumulative weights in value trees (based on [BeSt02, 140])

The relevance of a criterion is eventually computed from the product of its relative weight and the relative weight of its parent and the parent's parent and so forth. Reflecting the true relative importance to all given criteria, this value is called *cumulative weight*. We note that consistency has to be taken care of at every stage of assessment [BeSt02, 139], [Saat80, 78].

Regarding the sample scenario, we assume cardinal values for weights are given *a priori* and are subject to change as a measure taken by the trading entity. Furthermore, we will always elicit weights from the relative value of underlying preferences and implicitly include a consistency check (Figure 18).

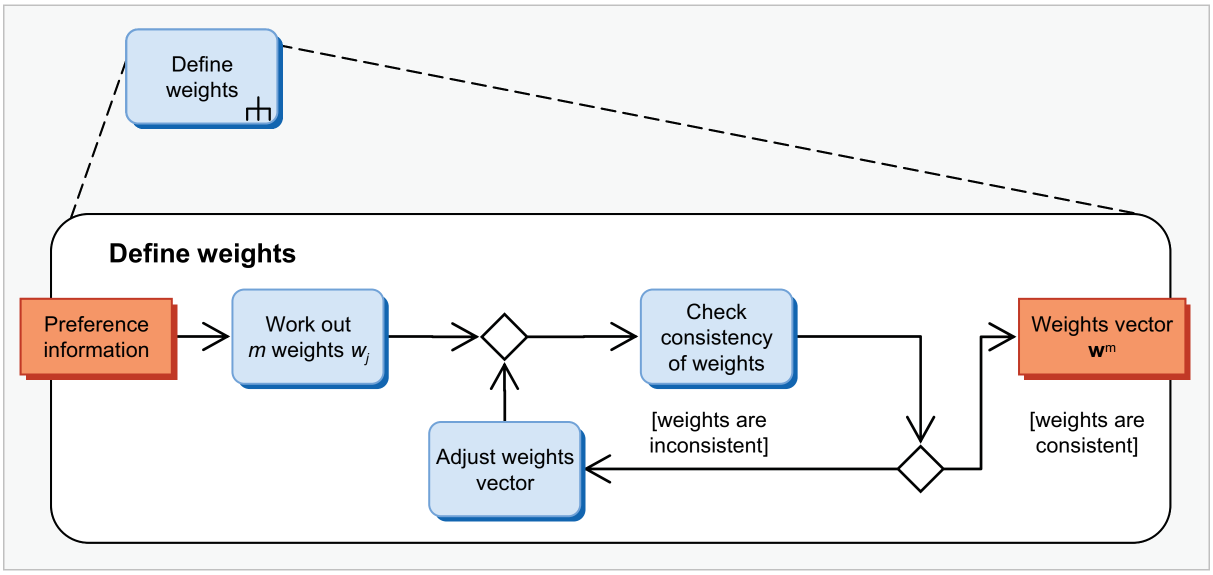

Figure 18: The subprocess of defining weights

3.3 Multiple Attribute Decision Making

3.3.1 A Taxonomy of MADM Methods

MADM methods are used when a *finite* (and countably small) number of alternatives with associated information on regarded criteria is given. The type of information provided by the DM influences the choice of method: Is preference information available or not and if so, what characterizes the salient feature of information (Figure 19) [ZiGu91, 29], [HwYo81, 8]?

We start with a description of methods which do not need explicit preference information (Subsection 3.3.2) or merely ask for aspiration levels (Subsection 3.3.3), before we turn to approaches which require ordinal preference information (Subsection 3.3.4) or cardinal preference information (Subsection 3.3.5).

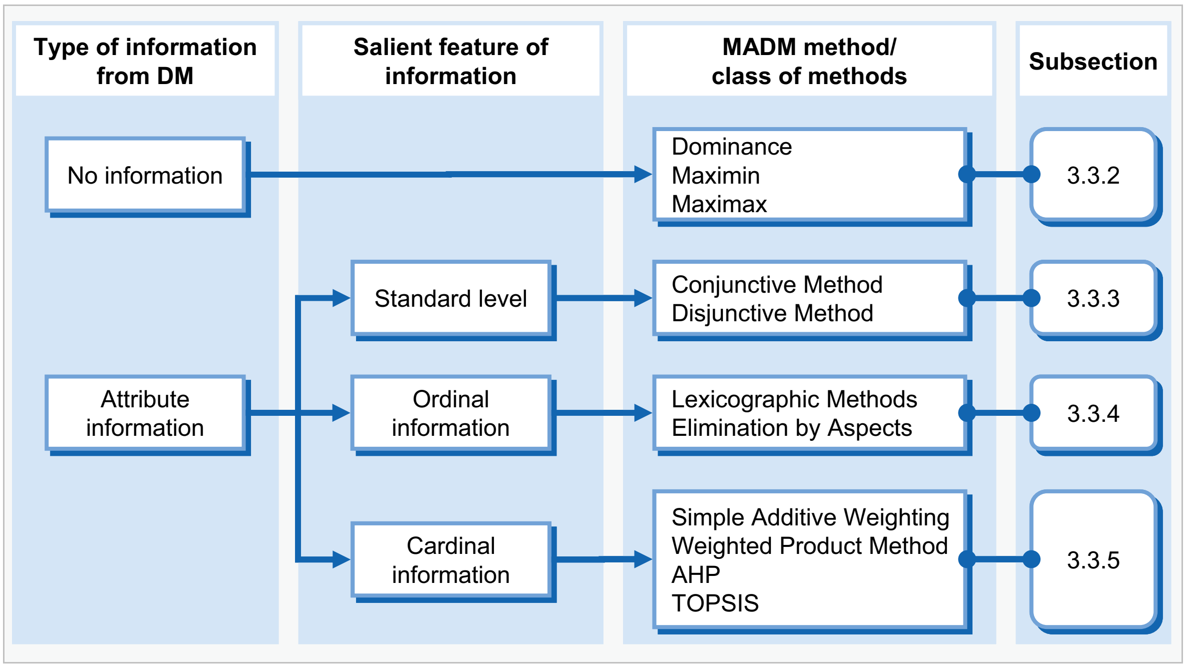

Figure 19: Overview of MADM methods (based on [HwYo81, 6])

3.3.2 Deciding without Preference Information

3.3.2.1 Absence of Attribute Relevance

When no information on the DM's preference structure is given, a distinction between the relevance of all attributes is not possible. For all the methods following, advantages of one attribute cannot be traded for disadvantages of another; thus, trade-offs are not permitted. These methods are called *non-compensatory,* contrary to *compensatory* ones which allow offsetting superior with inferior values [YoHw95, 17].

3.3.2.2 Dominance Principle

The *Dominance* principle reduces the number of alternatives in a given set [Macc73, 31]. An alternative is *nondominated* if there is no other one in the set which excels it in at least one attribute while being equal in all other ones. All nondominated alternatives constitute the *efficient frontier*, the subset of Pareto efficient alternatives which should be taken into further consideration [KeRa93, 70].

In contrast, an alternative is called *dominated* when in comparison to another one it is defeated in at least one attribute while not excelling in another one. Dominated alternatives play no role for further decision-making and can be eliminated from the set of alternatives [BeSt02, 83], [YoHw95, 18].

The graph below depicts a constellation with two attributes, where alternatives A and C are nondominated (they lie on the efficient frontier), and alternative B is defeated in both attributes by alternative C. The fictitious alternative D lies beyond the efficient frontier and is called *unfeasible* (Figure 20).

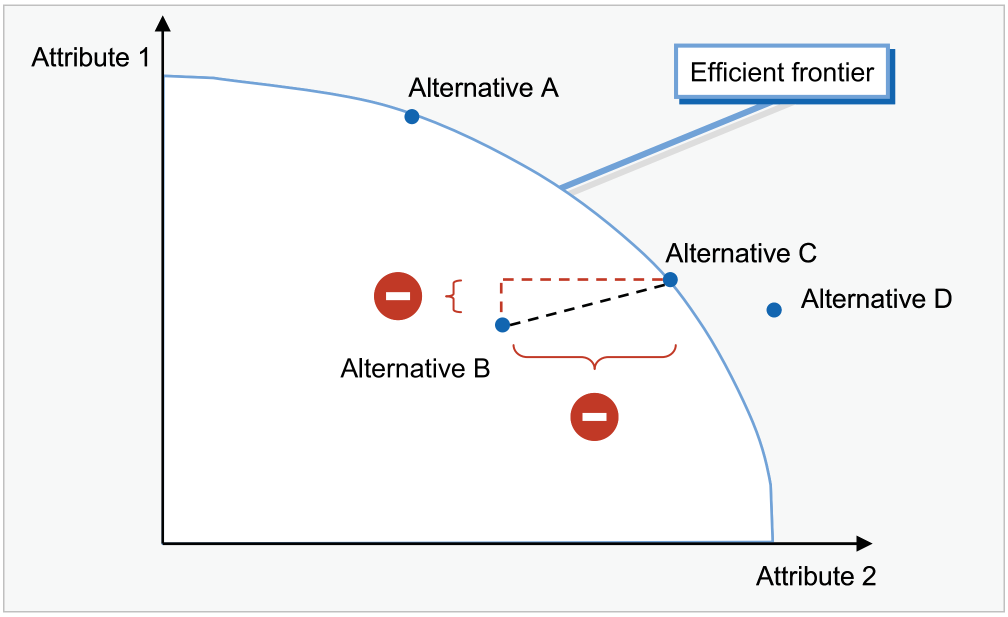

Figure 20: Efficient frontier (based on [KeRa93, 71])

The Dominance principle can be used as a first-stage filter to isolate a subset of alternatives; with an increase in alternatives and attributes, it will less likely determine only one efficient option.

3.3.2.3 Maximin and Maximax

When the decision-making context provides a tendency of preference, either in terms of a pessimistic or optimistic attitude towards the alternatives, we can make use of the *Maximin* or the *Maximax* method. Both methods do not require additional information about the DM's preferences, but demand comparable attribute values, i.e. normalizing the attribute vectors in advance [ZiGu91, 43–44].

The *Maximin* method estimates the lowest value for each alternative and ranks all alternatives in descending order by their lowest value. The DM is advised to select the highest ranked alternative. This procedure is also called pessimistic, since only the lowest value is taken into account and (possibly) superior values of other attributes cannot balance the one weakness [YoHw95, 28].

The *Maximax* method works rather similar; instead of the lowest, it identifies the highest value for each alternative which serves as a ranking criterion. Again, the DM is supposed to select the highest ranked option. This method is called *optimistic*, as it focuses merely on the highest value and disregards other inferior attributes [YoHw95, 30].

Table 9: Maximin and Maximax decision rules [YoHw95, 28–30]

Method	Selection rule	Priority	Precondition
Maximin	$A^* = \left\{ A_i \middle\| \max_i \left(\min_j v_{ij} \right) \right\}$	Lowest value (pessimistic attitude)	For $\mathbf{A} \in \mathbb{R}^{n \times m}$ with $i = \{1,\ldots,n\}$; $j = \{1,\ldots,m\}$ and $v_{ij} \in \{ v_{ij} = v(a_{ij}) \| v \in [0;1] \}$.
Maximax	$A^* = \left\{ A_i \middle\| \max_i \left(\max_j v_{ij} \right) \right\}$	Highest value (optimistic attitude)	

Both procedures assign extreme weights of one hundred percent to one attribute (the lowest or highest) and of null percent to the remaining ones to determine the best alternative A^* (Table 9) [ZiGu91, 44–45]. The two methods do not by all means lead to an advice for a single alternative, and they are due to their narrow focus disputable when it comes to withdrawing all but one criterion (the weakest one in the Maximin and the strongest one in the Maximax method) to justify the made decision [Macc73, 29]. Thus, we remove them from our future scope.

3.3.3 Satisficing (Conjunctive and Disjunctive Approaches)

The idea of satisficing relates back to the work of Simon, who worked out the human inability of conducting rational behavior in decision-making. A DM rather concentrates on selecting an alternative which satisfies certain aspiration levels instead of seeking a global optimum [BeSt02, 104], [Simo66, 204–205].

The two types of heuristics based on satisficing are the *Conjunctive* and the *Disjunctive* approach. Whereas the former method is absolutely *non-compensatory,* the latter is diametrically opposite and perfectly *compensatory*. Instead of determining a single optimal solution, the two satisficing approaches divide the set of alternatives into two subsets of acceptable and unacceptable alternatives. While the latter are disregarded from further consideration, the former comprise the number of relevant solutions [YoHw95, 20].

Satisficing requires aspiration levels which have to be set carefully because the thresholds determine the size of the resulting subsets: If the cutoff values are set high (low), the number of acceptable alternatives diminishes (soars), and if the DM fails to retrieve a feasible solution, he most likely will lower the aspiration levels [YoHw95, 20–21], [Simo55, 111].

When alternatives have to exceed the thresholds of all attributes to be considered as acceptable solutions, we use the *Conjunctive* approach. In this case an alternative is unacceptable, if at least one of the corresponding values fails to meet the minimum requirements [ZiGu91, 47].

The *Disjunctive* approach is less demanding than the Conjunctive one; the set of acceptable alternatives is defined by all alternatives which meet or exceed at least *one* threshold. Hence, the size of the subset of acceptable alternatives is much larger than the one in the Conjunctive approach [YoHw95, 21–22]. An overview of both heuristics and the formal relation to the given cutoff values a_j^o is given below (Table 10).

Table 10: Satisficing approaches [ZiGu91, 47–48]

Method	**Acceptance rule**	**Main implication**	**Precondition**
Conjunctive	$a_{ij} \geq a_j^o \ \forall\, j$	Non-compensatory	For $\mathbf{A} \in \mathbb{R}^{n \times m}$ with $i = \{1,\ldots,n\}$; $j = \{1,\ldots,m\}$ and $a_j^o \in \mathbb{R}$.
Disjunctive	$\exists\, a_{ij} \in \{a_{ij} \geq a_j^o\}$	Compensatory	

Satisficing methods can be helpful to reduce the set of alternative and serve as a first-stage filter for the DM [ZiGu91, 48]. The combination of both methods may also work well as a comprehensive filter for creating rules in repetitive decision-making [BeSt02, 105], [YoHw95, 22].

3.3.4 Sequential Elimination

3.3.4.1 General Course of Action

The idea of determining the optimal solution by sequentially eliminating alternatives names the next two MADM methods. If ordinally ranked attributes are given, the

Lexicographic Methods (LM) compare alternatives attribute-wise and withdraw dominated options until a single one remains. Similar, when no order for attributes is provided, *Elimination by Aspects* (EbA) removes all alternatives which do not satisfy attribute-wise standards until all but one are discarded.

3.3.4.2 Lexicographic Methods

The name reflects the way this approach works: like words in a dictionary, alternatives are ranked step-wise (where words consist of letters, alternatives have attributes). In case specific attributes predominate others by importance, the DM can quickly estimate an optimal solution: Beginning with the most important attribute, we rank the alternatives and eliminate all but the best one. If more than a single alternative prevails, we repeat ranking and eliminating with the next most important attribute. The iteration stops when only one option remains [ZiGu91, 49–50].

Formal: Let *n* be the number of alternatives *A*, and *m* be the number of attributes to be maximized. Let *k* be the iteration step and $\left\{A^0\right\}=\left\{A_j\right\},\ j\in\left\{1,\ldots,m\right\}$, we denote the rule

$$\left\{A^k\right\}=\left\{A^{k-1}\middle|\max_j\ x_{kj}\right\},$$

which is repeated until $\left\{A^k\right\}=1$ or $k=n$, when all attributes have been used in the process and the final set of alternatives $\left\{A^n\right\}\neq 1$ is considered as equivalent [Webe93, 68]. A further explication of the formal background of LMs is given in [Fish74].

The improved *Lexicographic Semiorder* (LS) has its foundations in the work of Tversky and Luce [Tver69, 32], [Luce56, 181–182]. It uses the same procedure as the LM but requires significant differences between compared attributes before judging an alternative as dominating. In addition to the ranking of attributes, threshold levels are needed for attribute-wise comparisons [ZiGu91, 50–51].

LMs are intuitive, easily understandable, and do not require normalization of attribute ratings; their disadvantage is the neglect of lower ranked attributes, which cannot compensate for low values on higher ranked attributes [ZiGu91, 50], [Tver69, 46].

3.3.4.3 *Elimination by Aspects*

The EbA method has been initially proposed by Tversky and is similar to LMs, but the basic prerequisites differ in terms of information on attributes [Tver72, 285–287]: Instead of a ranking order, so-called *standards* for satisfaction have to be given. To attain the order for the *aspect*-wise elimination of alternatives, we investigate the *ability of discrimination* for each standard. This ability is determined by the number of alternatives eliminated by applying the standard of an aspect on the present set of alternatives. Thus, we begin eliminating with the aspect that discards the most alternatives and continue until one element remains [ZiGu91, 51–52].

Formal: Let n be the number of alternatives A, and m be the number of attributes to satisfy a specified standard. Let k be the iteration step with descending ability of discrimination so that $\left\{A^k\right\} \leq \left\{A^{k-1}\right\}$, and with $\left\{A^0\right\} = \left\{A_j\right\}$, $j \in \{1,\ldots,m\}$, we denote the rule

$$\left\{A^k\right\} = \left\{A^{k-1} \middle| \text{satisfies } x_{kj}\right\},$$

which is repeated until $\left\{A^k\right\} = 1$ or $k = n$, when all attributes have been used in the process and the final set of alternatives $\left\{A^n\right\} \neq 1$ is again regarded as equivalent [YoHw95, 26].

The *EbA* approach combines ideas of the Conjunctive method and the LM: The practical application is lexicographically motivated and the elimination decision is based on the satisfaction of specified standards. But the relevance of attributes is completely ignored, and elimination happens rather arbitrarily than in a rational way [Webe93, 72], [ZiGu91, 52]. Tversky admits the inappropriateness of his method for many cases in the original work as well [Tver72, 298].

3.3.5 Value Function Methods

3.3.5.1 *Synthesizing Partial Values*

A well-known family of methods synthesizes partial value functions in order to determine a complete preorder of alternatives [Roy05, 15]. The calculation of an aggregate measure expects cardinal scaled information on the attribute outcomes as well as weights for each attribute; how this vector of information is finally summarized into a scalar depends on the specific approach used [Tria00, 5]. This Subsection outlines the following four prominent methods: the *Simple Additive Weighting (*SAW*),* the *Weighted Product Method (*WPM*),* the *Analytical Hierarchy Process (*AHP*)*, and the *Technique for Order Preference by Similarity to Ideal Solution (*TOPSIS*).*

3.3.5.2 Simple Additive Weighting and Weighted Product Method

The SAW approach, sometimes also referred to as the Weighted Sum Method, is particularly appealing due to its simple application [BeSt02, 87], [YoHw95, 32]. The step-by-step course of action is illustrated below (Figure 21). The SAW method assumes underlying additive value functions and computes an alternative's score $V_i = V(A_i)$ by adding weighted normalized values $w_j v_{ij} \; \forall j = \{1,\ldots,m\}$ before eventually ranking alternatives on this aggregate (Table 11, p. 47).

Two additional preconditions are fundamental for this technique, the *preferential independence* of partial values and the assessment of weights in proportion to the relative value of the criterion [YoHw95, 33], [Wins94, 773–774]. As we only determine weights from aggregating conversion ratios, the second precondition is of less importance here.

Apart from that, preferential independence relates to the absence of interdependencies between the partial value functions: This means the contribution of an individual attribute value to the aggregate is not affected by any other attribute [Dyer05, 274–275], [KeRa93, 129]. Proof of this necessary condition is given in [Fish76, 248].

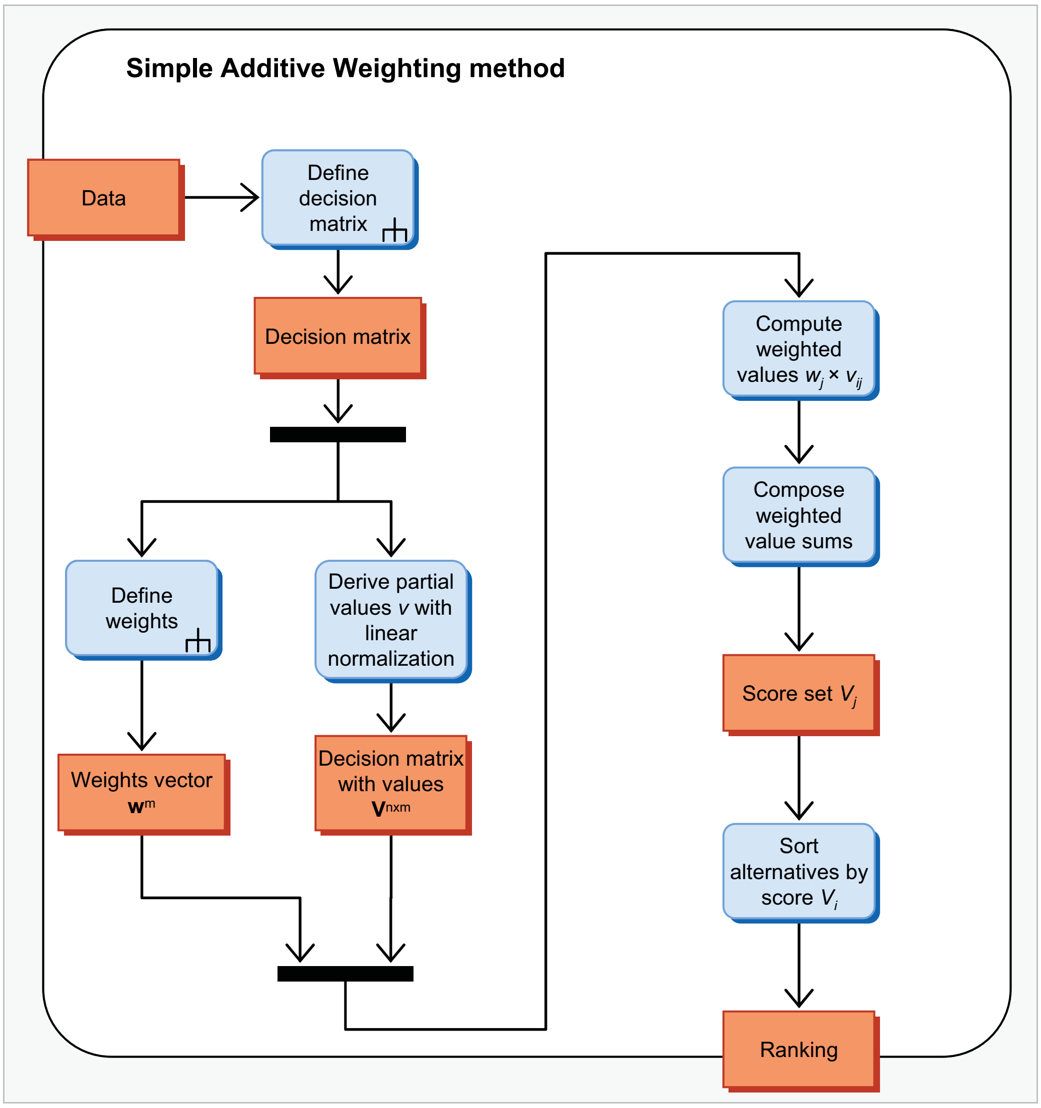

Figure 21: Process of the Simple Additive Weighting method

Though the requirements of the SAW appear to be modest, preferential independence tends to be violated in concrete situations. Then the assessment of linear value functions leads merely to an approximation [BeSt02, 103], [BMP+00, 109]. In response, non-additive synthesizing approaches are proposed (for a discussion see [DySa79]).

One of these, the Weighted Product Method, composes the score of an alternative by multiplying criteria values (Table 11) [YoHw95, 36]. The algorithm varies in several steps from the SAW (Figure 22) and requires values greater than one to avoid distorted results.

Mixing different scales blurs the result of the multiplication and complicates interpretation; as a reference point, we need to determine a fictitious upper bound A^* comprising of the best given values for each outcome.

Formally, we denote for the score of this alternative

$V\left(A^*\right)$ with $v_j^* = \max v_{ij}$.

As a result, the value ratio between an alternative and the upper bound, scaled from one to zero, serves as a composite score: The proximity to one indicates the preference of an option and makes ranking alternatives possible [YoHw95, 37].

Table 11: Additive and multiplicative weighting approaches [Dyer05, 286], [YoHw95, 36–37]

Method	Score computation	Precondition
Simple Additive Weighting	$V_i = \sum_{j=1}^{m} w_j v_{ij}$	For $\mathbf{V} \in \mathbb{R}^{n \times m}$ with $i = \{1,\ldots,n\}$; $j = \{1,\ldots,m\}$; $v_{ij}, w_j \in [0;1]$
Weighted Product Method	$\frac{V_i}{V\left(A^*\right)} = \frac{\prod_{j=1}^{m} \left(v_{ij}\right)^{w_j}}{\prod_{j=1}^{m} \left(v_j^*\right)^{w_j}}$	For $\mathbf{V} \in \mathbb{R}^{n \times m}$ with $i = \{1,\ldots,n\}$; $j = \{1,\ldots,m\}$; $v_{ij} \in \mathbb{R} \wedge v_{ij} \geq 1$; $v_j^* = \max v_{ij}$; $w_j \in [0;1]$

Both methods allow compensation between partial values: whereas the normalization of values facilitates balancing, different original scales inhibit trade-offs. Combining value functions in additive or multiplicative ways seems sound, but determining weights and identifying correct values is difficult. Preference independence is also questionable – it is rather subject to the individual situation whether a strength is able to balance a weakness completely [BMP+00, 109].

The advantage of both approaches is the ease of their scoring algorithms: Although reference points have to be re-calculated, an increase in alternatives or attributes may quickly be incorporated (either in terms of the *a priori* normalization or in terms of updating the *a posteriori* ideal alternative) [BMP+00, 105]. Moreover, an additive function can be more easily communicated and constructed than multiplicative models [BeSt02, 103].

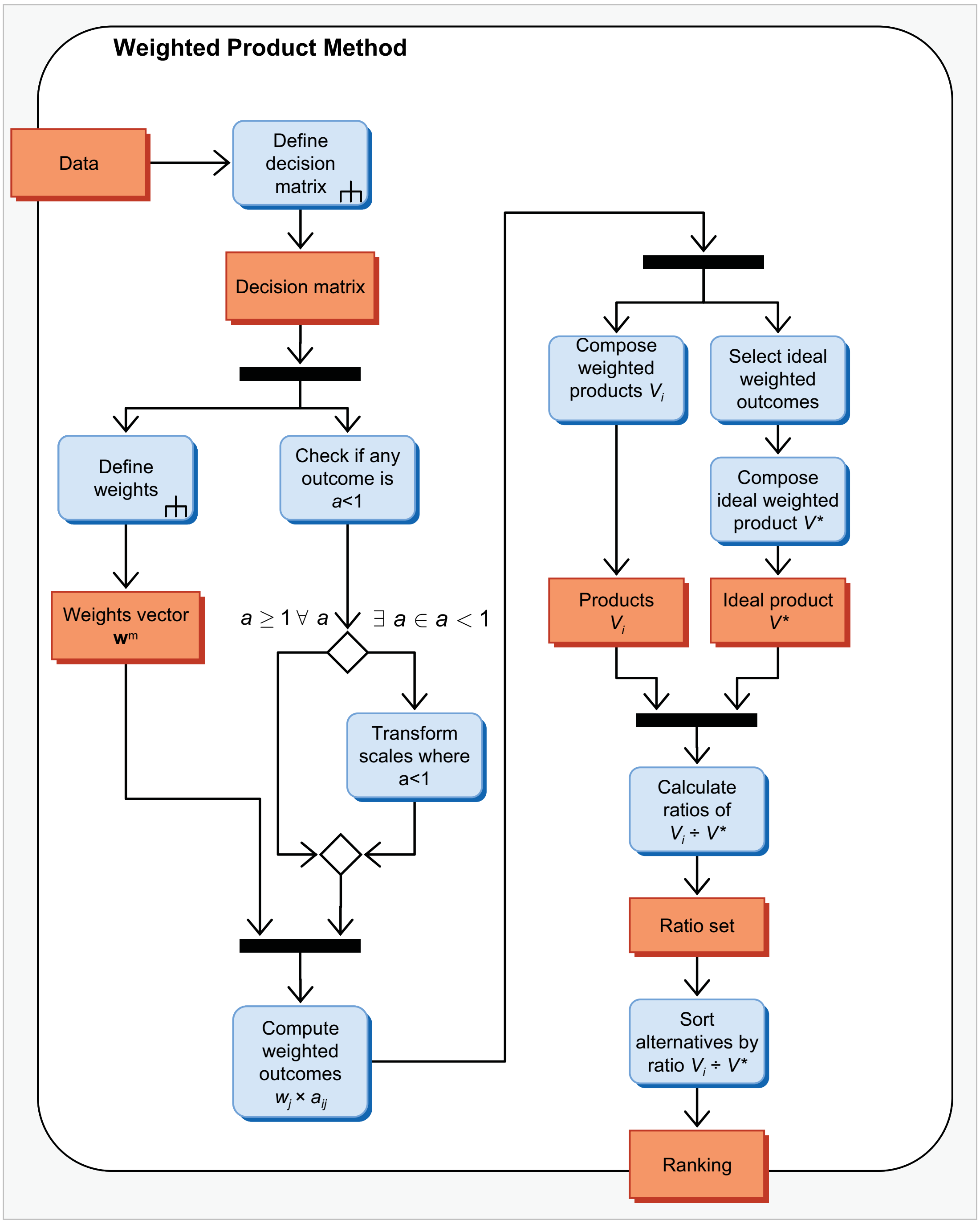

Figure 22: Process of the Weighted Product Method

3.3.5.3 Analytic Hierarchy Process

The Analytic Hierarchy Process, developed by Thomas Saaty, describes a full methodology of tools for decomposing and synthesizing complex decision situations [Saat05, 347], [Saat80, 3]. The AHP visualizes the MCDM problem in hierarchical structures and facilitates identifying relations between preferences, criteria, and alternatives. The composite score for each alternative is finally derived from a constructed decision matrix [Tria00, 9]. The AHP is a very popular method, and numerous documented examples of its application to a wide scope of decision problems can be found in scientific literature; interesting insights are provided by [VaKu06], [Varg90].

A hierarchy structure consists of at least three levels: the goal on top, several criteria in the middle, and potential alternatives on the bottom [Saat80, 43]. Intermediate levels may be modeled to represent subordinate goals or criteria (Figure 23); examples for four- or five-level hierarchies can be found in [Saat05, 359–382], [Saat80, 132–138], [Saat80, 142–156]. *Edges* between *nodes* imply the contribution of the subordinate aspect to the superior one and may be left out if no relation exists.

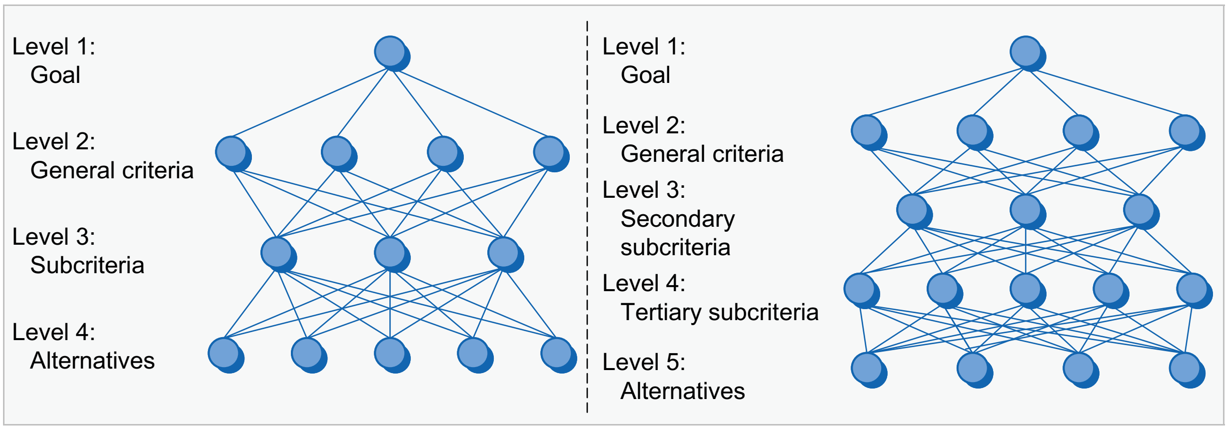

Figure 23: Generic four- and five-level hierarchies [Saat80, 43], [Saat05, 362]

The process of the AHP is as follows (Figure 24):

At the beginning, the DM sketches the hierarchy and estimates the contribution of each aspect to the superior one, i.e. the *relative importance* with respect to a particular reference is determined in pairwise comparisons. Saaty suggests a nine-point intensity scale to indicate the degree of preference, although investigations of Belton and Gear have shown that rather a modified scale is needed to retain stable results [Dyer90, 252–254], [BeGe83, 229], [Saat80, 53–57]. We stick here to the original, heavily disputed scale without going into detail [HaVa90, 271], [Saat90, 265–266]. Estimating contributions of aspects explicitly includes not only criteria, but also the subordinate alternatives.

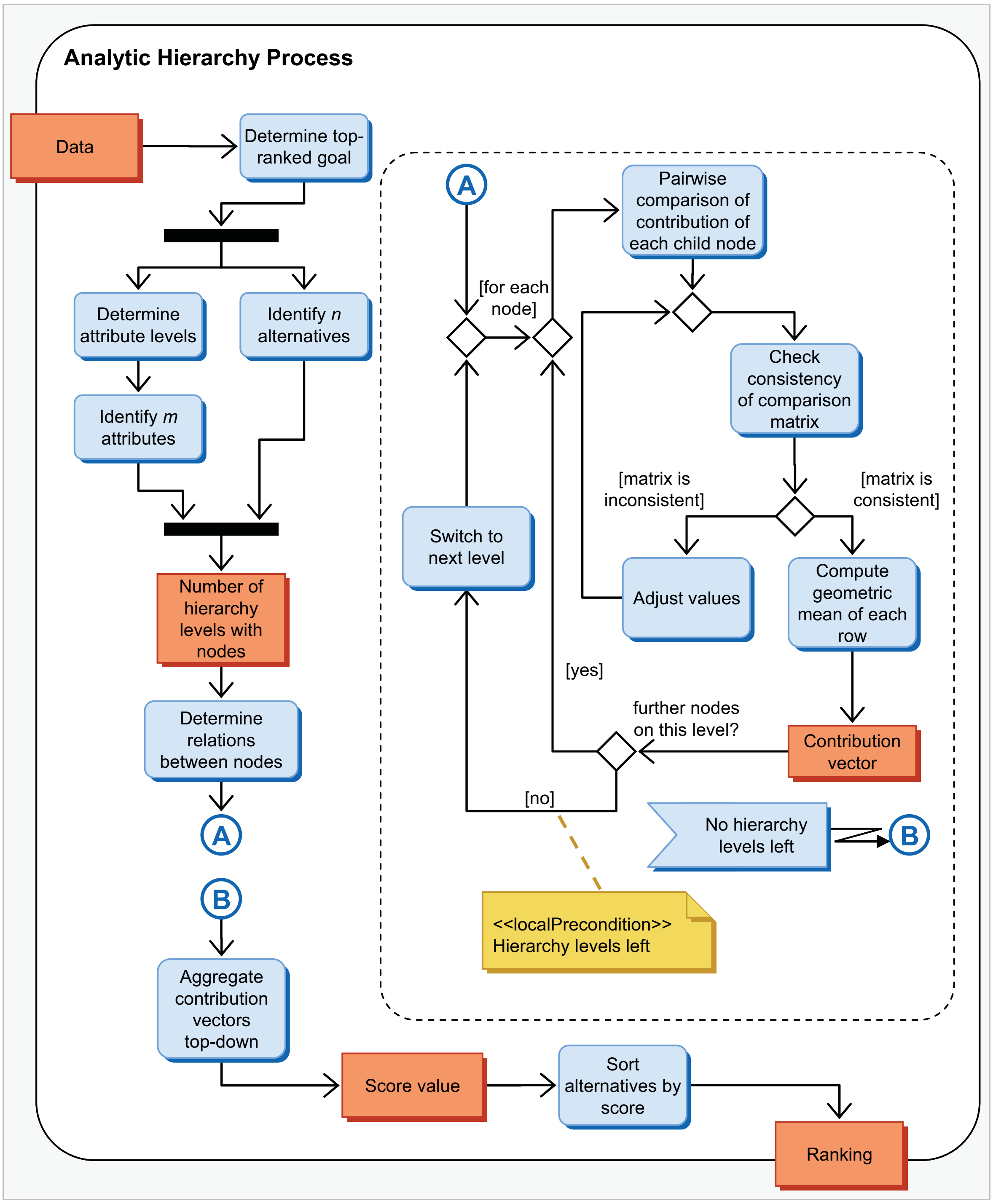

Figure 24: Simplified process of the Analytic Hierarchy Process

When a comparison matrix is estimated, consistency is checked, and the geometric mean of each row is computed and normalized to retrieve a vector with weight values. Each value is represented by an edge in the hierarchy between nodes on two levels. The comparison matrices on the next levels are estimated in the same manner, leading to weight values for each connecting edge [ZiGu91, 69–73], [Saat05, 348].

The score of an alternative is retrieved from the sum of weight values, which are multiplied with superior weight values in the same way we determined cumulative from relative weights before (cf. Subsection 3.2.3, p. 37).

The formal computation of a three-level hierarchy problem with m criteria and n alternatives requires $m \times [n(n-1)+(m-1)] \div 2$ pairwise comparisons, e.g. for our itinerary decision with three criteria and three alternatives, twelve values have to be computed from *solving twelve linear programs* (Figure 25).

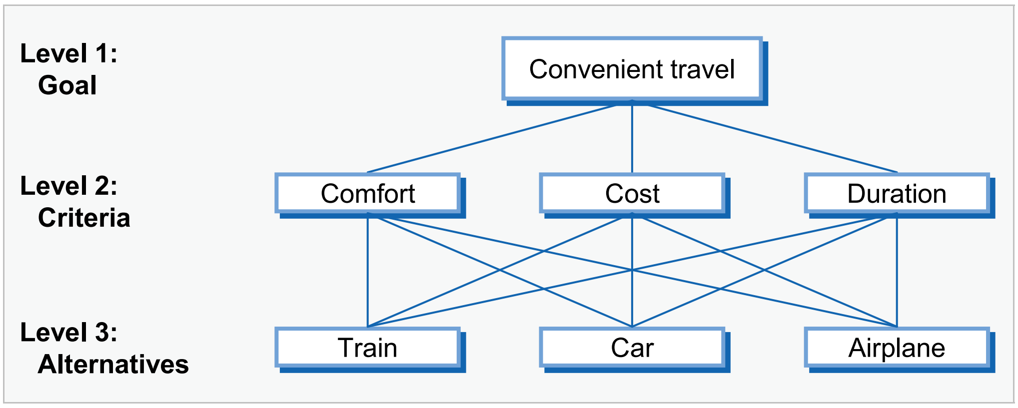

Figure 25: A three-level hierarchy for means of travel (based on [Saat80, 43])

The AHP is similar to the SAW method: Instead of normalized absolute values, relative ones are used in the AHP to compute an additive score [Tria00, 10]. But when an alternative with its criteria is very close to another one, the final score is distorted and the ranking becomes instable. This is called the "rank reversal" problem [BeSt02, 159], [BeGe83, 229]; crucial points are outlined in [ZiGu91, 90–91], [Dyer90]. In contrast, the advantages of the AHP lie in structuring complex situations and estimating weights for non-measurable criteria [Saat05, 347].

3.3.5.4 Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

The *Technique for Order Preference by Similarity to Ideal Solution* (*TOPSIS*) has been proposed by Hwang and Yoon as a MADM instrument for measuring relative efficiency of alternatives [HwYo81]. The method is comparably easy to use and supports conducting transparent decision-making in concrete situations. Application examples can be found in the areas of inter-company comparisons ([DYWi00, 968–971]), public transport evaluation ([FeWa01]), location decisions ([Chu02]) or industrial planning ([YuCo03]).

The name of the approach does not fully reflect the process: It determines the preference order on the grounds of the similarity to a positive ideal solution *and* the dissimilarity to a negative solution. Computing the distance of each considered alternative to those ideal solutions makes use of the Euclidean distance vector; for the two-attribute case this is depicted below using a two-dimensional coordinate system (Figure 26) [HwYo81, 128].

Though alternative one is closer to the positive ideal solution than alternative two, the approach may still favor the latter due to the greater distance to the negative ideal solution compared to alternative one.

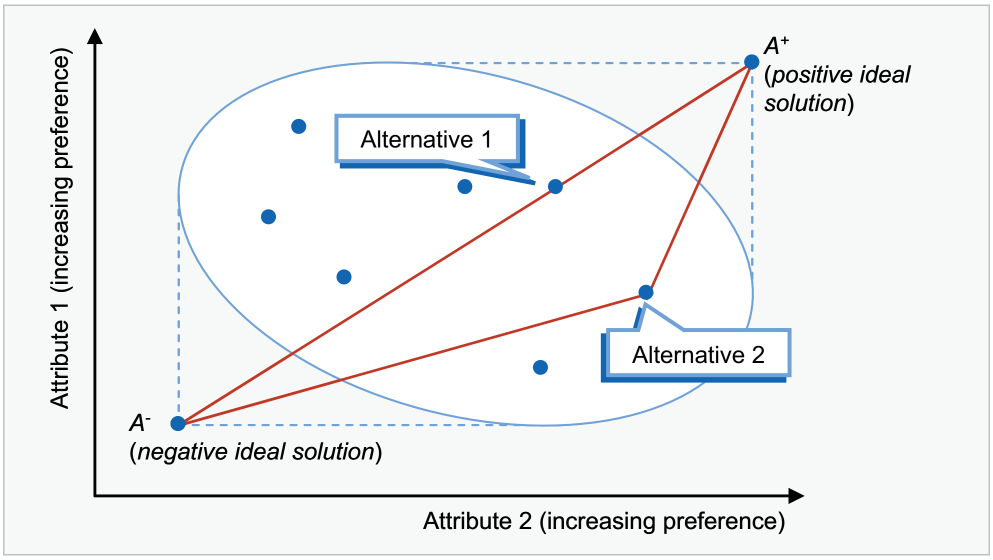

Figure 26: Euclidean distances to the ideal solutions in two-dimensional space [HwYo81, 129]

Therefore, if we want to rank alternatives with respect to two reference points, we have to construct these boundaries in advance. The step-by-step procedure is outlined below (Figure 27).

First, starting with a given decision matrix, we need to get comparable values v_{ij} in each matrix entry. This is achieved with a modified vector normalization and multiplication with the corresponding weights w_j [FeWa01, 465], [HwYo81, 131].

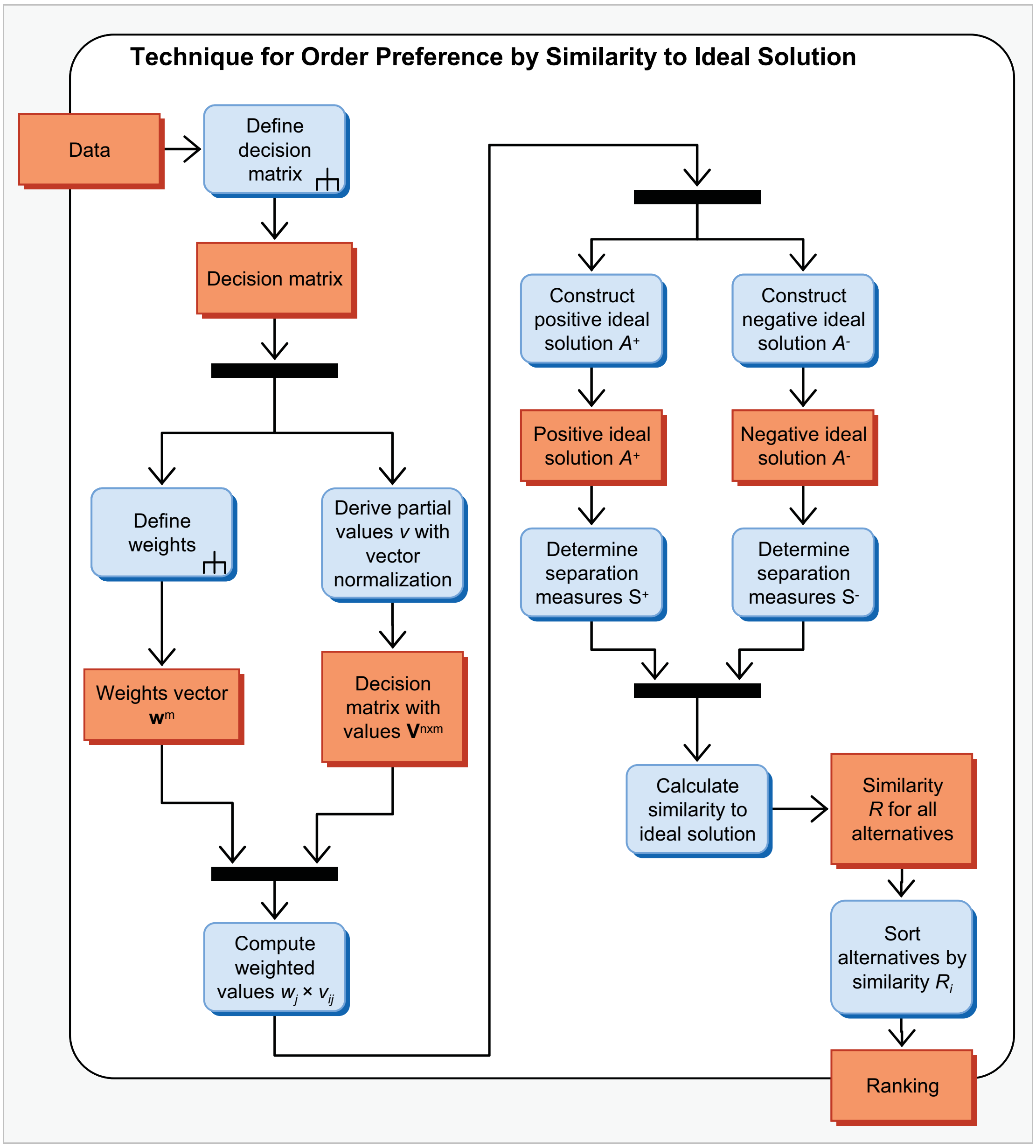

Figure 27: Process of the Technique for Order Preference by Similarity to Ideal Solution

In the second step, we construct two virtual ideal alternatives, A^+ consisting of all best criteria values v_j^+ (the positive ideal solution), and the negative ideal solution A^- with all the poorest values v_j^- (Table 12) [HwYo81, 131].

Table 12: Assembling positive and negative ideal solutions [HwYo81, 131]

	Values	**Precondition**
Positive ideal solution	$A^+ : v_j^+ = \left\{\max_i \left\{v_{ij} w_j\right\}\right\}$	For $\mathbf{V} \in \mathbb{R}^{n \times m}$ with $i = \{1,\ldots,n\}$; $j = \{1,\ldots,m\}$ and $v_{ij}, w_j \in [0;1]$
Negative ideal solution	$A^- : v_j^- = \left\{\min_i \left\{v_{ij} w_j\right\}\right\}$	

These two vectors represent extreme points in a Cartesian coordinate system, and all given alternatives are located between them, i.e. all alternatives can be constructed from linear combinations of these points (Figure 26). The method makes use of this particular feature: in the third step, we compute *separation* measures S^+_i (S^-_i) as indicators for the distance of each alternative from the positive (negative) reference point [HwYo81, 132].

$$S_i^+ = \sqrt{\sum_{j=1}^{m}\left(w_j v_{ij} - w_j v_j^+\right)^2}\ \forall\, i = \{1,\ldots,n\}\quad S_i^- = \sqrt{\sum_{j=1}^{m}\left(w_j v_{ij} - w_j v_j^-\right)^2}\ \forall\, i = \{1,\ldots,n\}$$

We do not rely merely on the closeness to the positive ideal solution but rather on both distances, since the shortest positive difference does not necessarily mean it is also least close to the negative ideal one; the distance vectors depicted above (Figure 26) illustrate a case in which one alternative (*number one*) is closer to the positive ideal *and* to the negative ideal solution then another one (*number two*).

The fourth step is concerned with computing the *similarity to ideal solution* measure and ranking the alternatives. Given the two distance indices for each alternative, we calculate the similarity measure R_i as follows [HwYo81, 132]:

$$R_i = \frac{S_i^-}{S_i^+ + S_i^-}\ \forall\, i = \{1,\ldots,m\} \text{ with } R_i \in [0;1]$$

The closer the similarity measure R_i is to one, the more preferable is the alternative; with a decreasing (increasing) difference to the negative (positive) ideal solution, the alternative becomes the less interesting [HwYo81, 132].

Fifth and finally, we can sort our alternatives in ascending order by the similarity measure and recommend the top-ranked option [HwYo81, 132].

Advising DMs with the help of a TOPSIS evaluation seems very appealing and applicable in concrete situations; reason is the similarity to the SAW method [HwYo81, 135–136]. Meanwhile, the method has been extended to situations with continuous solution sets, which usually require extensive linear programming [HLLi93, 890].

But a problem arises when cardinal values are not given or when the underlying utility is not subject to monotonicity [HwYo81, 137]. As we already ruled out the latter in our definitions (cf. Subsection 2.6.4), one may feel tempted to solve the former by transforming ordinal or nominal information. Unfortunately, this may lead to distortion (e.g. when intervals between values are not constant); in this case the technique may become a merely superficial recommendation (cf. also Subsection 3.2.1). On top of that, Wang and Triantaphyllou claim to have found evidence that the TOPSIS method also suffers from ranking irregularities (cf. AHP, Subsection 3.3.5.3) [WaTr08, 46].

3.4 Multiple Objective Decision Making

3.4.1 Overview of MODM Methods

In contrast to MADM methods, the set of alternatives in Multiple Objective Decision Making is not pre-defined: To cope with an infinite or continuous space of options, specified constraints and objective functions define the domain from which an optimal solution is to be "designed". [ZiGu91, 25], [HwMa79, 6–7].

Such decision problems, in which multiple objectives are to be optimized, have been initially referred to as *vector maximum problems* [KuTu51, 488].

In MODM, the DM's preference information is implemented in terms of aspiration or satisfaction levels for criteria. These levels may either be minimum (maximum) prerequisites when the corresponding objective is to be maximized (minimized), or an exact value which should be hit as close as possible [BeSt02, 210].

Hwang and Masud classify MODM methods on the type of information needed (Figure 28). A full introduction into the foundations of MODM and the classified methods can be found in their monograph [HwMa79].

Of these classes of methods, we will sketch the idea of Goal Programming in the following Subsection.

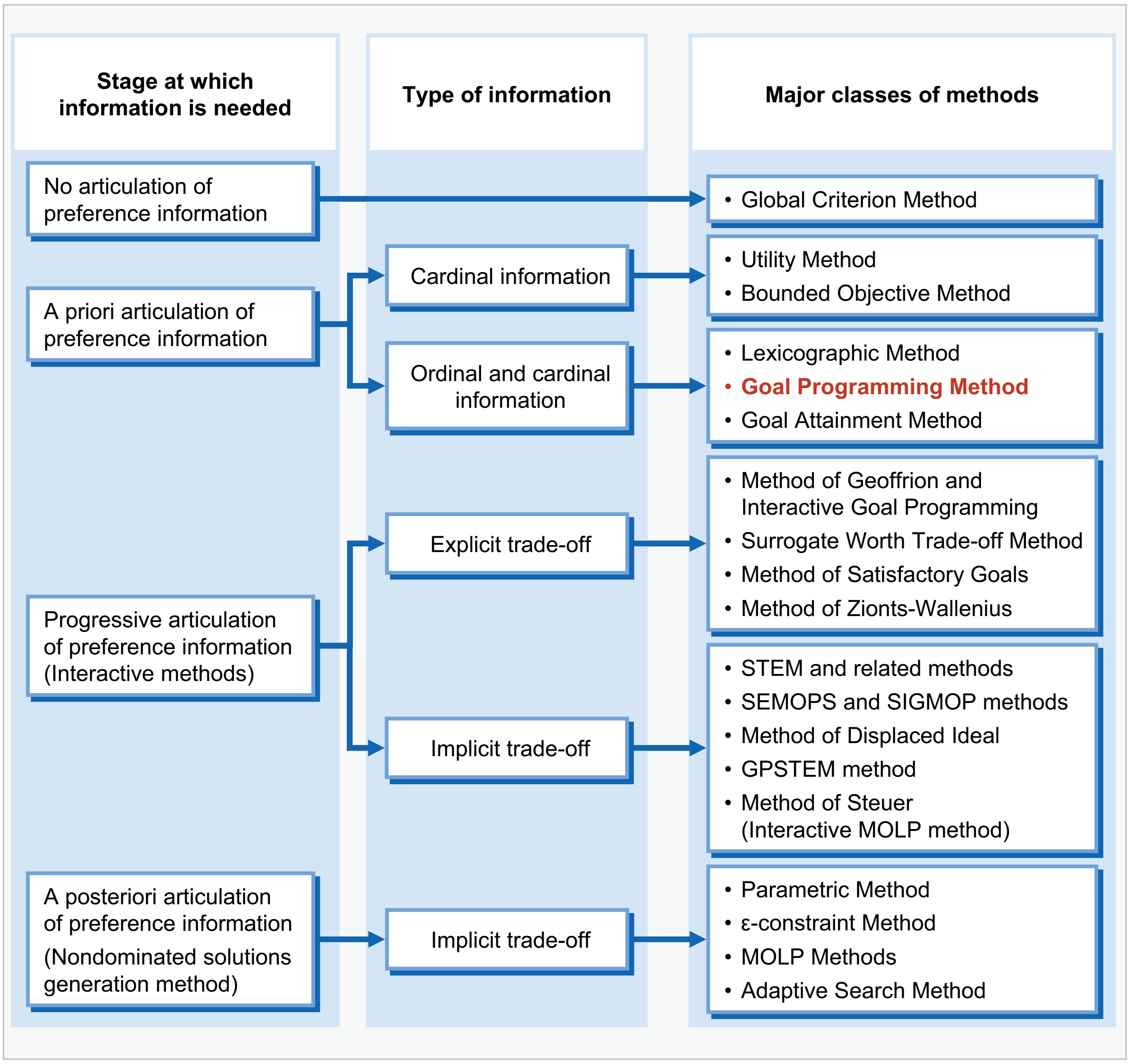

Figure 28: A taxonomy of methods for Multiple Objective Decision Making [HwMa79, 8]

3.4.2 Goal Programming

The first *Goal Programming* (GP) practice can be traced back to Charnes et al. who estimated a fair compensation for company executives [CCFe55]. Later, Charnes and Cooper developed the basic concept of GP as means for “goals, even when they are unattainable within the limits of available resources” [ChCo67, 215].

The GP technique has since then received wide acceptance in various fields, e.g. 265 reference cases can be found in [JoTa02, 134–136] and a bibliography of 443 classed entries is provided by [Rome91, 100–105].

The basis of GP is a linear programming problem with the following constraints presented in [ChCo67, 216]:

$$
\begin{array}{rcrl}
3\,x_1 & +2 & x_2 & \leq 12 \\
5\,x_1 & & & \leq 10 \\
x_1 & + & x_2 & \geq 8 \\
-x_1 & + & x_2 & \geq 4 \\
x_1, & & x_2 & \geq 0
\end{array}
$$

Depicting the problem with its constraints reveals two (orange and blue) shaded areas with partly feasible solutions, but since both subsets do not overlap, no set of feasible solutions exists which satisfies all constraints (Figure 29) [ChCo67, 217].

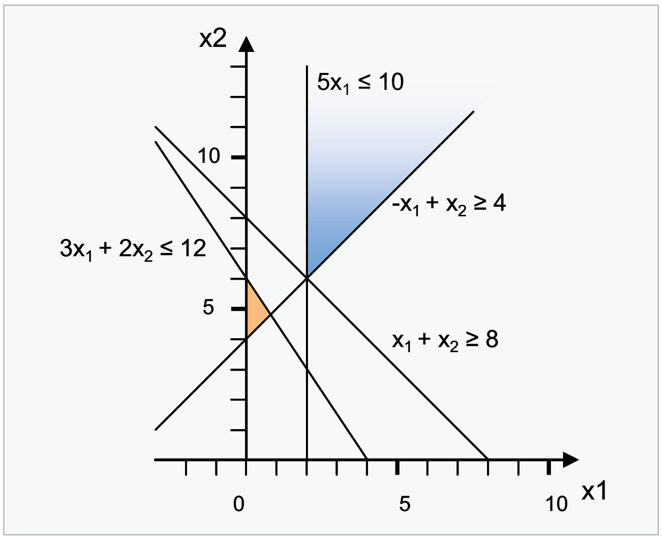

Figure 29: Portray of feasible solutions in a GP example [ChCo67, 216]

Now, the GP idea is to introduce two deviation variables d_i^- (for underachievement) and d_i^+ (for overachievement) when measuring the attainment of a target t_i by an objective i [Lee99, 8-2–8-3]. Then we seek to minimize an achievement function z that consists of the weighted deviations of all q objectives. We can denote the linear GP problem as

$$
\begin{array}{lll}
\min & z = \sum_{i=1}^{q}\left(nw_i d_i^- + pw_i d_i^+\right) & \\
\text{subject to} & f_i(x) + d_i^- - d_i^+ \quad = t_i & \forall i = \{1,\ldots,q\}, \\
& nw_i, pw_i, d_i^-, d_i^+ \quad \geq 0 & \\
& nw_i \cdot pw_i \quad = 0 &
\end{array}
$$

under the assumption all objectives are normalized [JoTa02, 130–131]. Since we model relative importance between objectives by applying weights (nw_i, pw_i), this particular type of GP problem is called *weighted GP* or *Archimedean GP* [JoTa02, 130], [ZiGu91, 122]. The modified simplex method solves this problem [Lee72, 105–106].

In the wide array of GP extensions, two other major variants stand out notably often: *Lexicographic* (or *preemptive*) *GP* and *Chebyshev* (or *minmax*) *GP* [Lee99, 8-4–8-6], [Igni85, 12–13].

Preemptive GP strives to attain objectives in a predefined priority order and is helpful when the DM cannot quantify the relative importance of goals. As the approach does not allow trade-offs between priority levels, the DM should have a natural order of objectives in mind [JoTa02, 132]. Preemptive GP is solved by a sequence of linear programs; a formal outline is given in [Lee99, 8-5–8-6].

Chebyshev GP aims at a shortcoming of Archimedean GP: if a large number of deviations are very small, few very large deviations do not preponderate in the attainment function. In order to ameliorate this inconvenience, the Chebyshev GP approach minimizes the maximum weighted deviation [JoTa02, 132–133], [ZiGu91, 124].

$$
\begin{array}{llll}
\min & z = Max & & \\
\text{subject to} & nw_i d_i^- + pw_i d_i^+ & \leq Max & \\
 & f_i(x) + d_i^- - d_i^+ & = t_i & \forall i = \{1, \ldots, q\} \\
 & nw_i, pw_i, d_i^-, d_i^+ & \geq 0 & \\
 & nw_i \cdot pw_i & = 0 &
\end{array}
$$

In result, the heuristic balances the levels of objectives instead of sticking to a strict minimisation of their sum. This reflects the attitude of a careful DM, similar to the Maximin approach in MADM (Table 9).

Currently, research on the issue of GP includes non-linear GP, fractional GP, integer GP and interactive GP. The integration and combination with other techniques such as the AHP or the *Data Envelopment Analysis* (DEA) plays also an important role [JoTa02], [Lee99]. In terms of the DEA, which determines an efficient frontier from a domain of alternatives, defining upper and lower bounds for weights and conducting sensitivity analysis are of interest (for an explication of the DEA method see the original work of [CCRh78]) [BeSt02, 303], [JKWa98], [Stew96].

GP operationalizes Simon's concept of satisficing insofar as functions for objectives are given and the DM specifies his aspiration levels (*goals*) (cf. p. 41). Though the technique is widely regarded as an "intuitive and comfortable approach", it is not flawless [BeSt02, 231]: setting realistic goals in advance can constitute a major pitfall and may lead either to "no alternative, or very large numbers of alternatives, which satisfy the goals" [Stew92, 576]. Especially when complex or unfamiliar problems are concerned, the DM will hardly be aware of specific target levels. Thus the use of GP is recommended for *screening purposes* i.e. for producing a subset of feasible alternatives [EhWi05], [Stew92, 578].

3.5 Decision Aids

3.5.1 Outranking Relations

The methods in this Section differ from the previous ones insofar, as they explicitly permit incomparable alternatives and criteria, and do not require transitivity or completeness in the arrangement of alternatives [BeSt02, 104–105], [Roy73, 181–183]. The intent of outranking is not so much retrieving an optimal solution but rather reducing the number of given alternatives to a non-dominated set from which the DM is supposed to select afterwards; for this reason these methods are called *aids* [ZiGu91, 202]. The relation between two alternatives A_1 and A_2 is assessed with the help of a binary *outranking relation S*, in comparing pairs of alternatives, which leads to three possible relations (Table 13) [Roy73, 181–182].

Table 13: Outranking relations [Roy73, 181–182]

Strict preference[1]	**Indifference**	**Incomparability**
A_1SA_2 and not A_2SA_1	A_1SA_2 and A_2SA_1	*Not* A_1SA_2 and not A_2SA_1
$A_1 \succ A_2$	$A_1 \sim A_2$	$A_1 \not\sim A_2$
A_1 is strictly preferred to A_2	A_1 is indifferent to A_2	A_1 is incomparable to A_2

1) applies to the inverse relation as well

The inclusion of incomparable relations is useful for modeling a preference order when the DM is incapable or unwilling to distinguish [Roy73, 182–183]. We outline the oldest family of methods, called *ELECTRE*, in the following Subsection [ZiGu91, 207].

Apart from ELECTRE, another class of methods named PROMETHEE (acronym for *Preference Ranking Organization METhod for Enrichment Evaluations*) is widespread in outranking research [BeSt02, 233]. For an introduction with latest developments we refer to [BrMa05] or the original publication [BVMa86].

3.5.2 The ELECTRE Approach

The family of ELECTRE methods was initially developed in 1965, and the first ELECTRE method was officially published three years later [Roy68]. The acronym ELECTRE is deduced from *ELimination Et Choix Traduisant la REalité* (*ELimination and Choice Expressing the REality*) [Tria00, 13], [Roy68]. For a summary of six ELECTRE methods, namely ELECTRE I, II, III, IV, IS, and TRI, we refer to [Vinc99, 11-5–11-10]. The oldest and simplest of these, ELECTRE I, is presented in this Subsection.

ELECTRE methods have been applied to a wide field of concrete decision problems, including environmental planning ([GSM+03], [SHLa98], [TeTz94]), employee recruitment ([SGKM07]), location planning ([Nore06], [BDLe90]), transportation management ([RoHu82]) and financial issues ([MKBe88]).

The underlying principle of ELECTRE is the following: We compare alternatives pairwise and assess the extent to which an alternative is outranking another *and* up to which extent this is *not* the case. In order to outrank an alternative, sufficient evidence *for* the assumption (*concordance*) and insufficient evidence *against* the assumption (*discordance*) are needed. The strength of an evidence is determined by the evaluation of constructed concordance and discordance measures for each comparison [ZiGu91, 207].

The course of action is illustrated below (Figure 30) and the five steps of the ELECTRE I method are described in the next paragraphs.

First, we need a normalized and weighted decision matrix, although incomparability is allowed; for ELECTRE methods, it is common practice to apply the vector normalization [Tria00, 13].

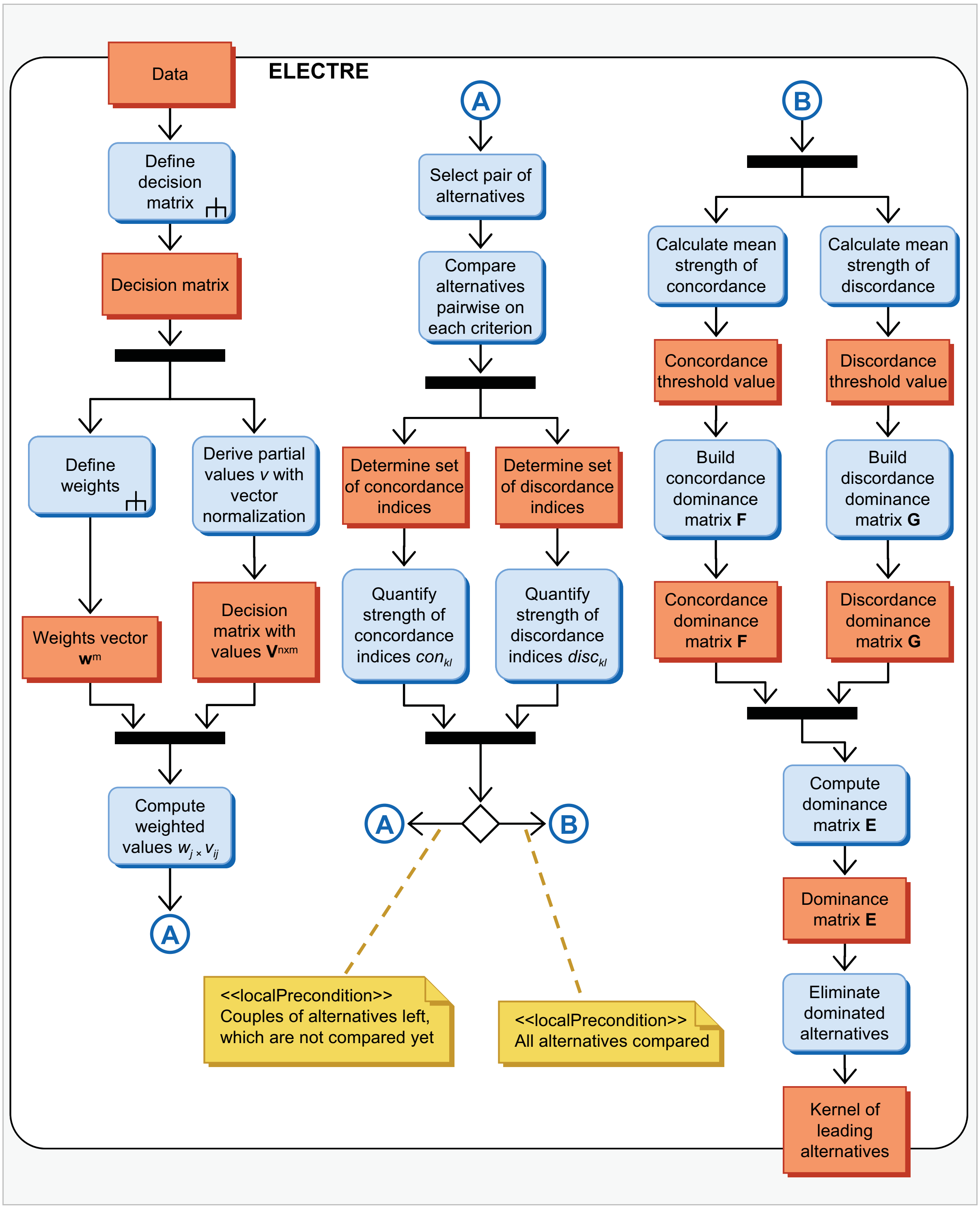

Figure 30: Process of the ELECTRE method

Secondly, the strength of concordance and discordance are determined for each couple of alternatives. The comparison of two alternatives is conducted using the outranking relation S on each j-th criterion separately, thus it is not as strict as the formal rules of the value function methods.

The strength of concordance con_{kl} for alternative A_k outranking alternative A_l is called *concordance index*. This measure is computed from the sum of weights associated with indices on which A_k outranks A_l [BMP+00, 135–137]:

$$con_{kl} = con(A_k S A_l) = \sum_{\{j:a_{kj} \geq a_{lj}\}} w_j \text{ with } k,l \in \{1,\ldots,n\} \wedge k \neq l$$

The *discordance index* represents the intensity of dissent against the assumption of A_k outranking A_l and is calculated from the maximum difference between criterion values on which A_l is outranking A_k [BeSt02, 110], [ZiGu91, 210]. Thus, we denote for the discordance index

$$dis_{kl} = dis(A_k S A_l) = \frac{\max\limits_{\{j:a_{kj} < a_{lj}\}} \left| w_j \cdot a_{kj} - w_j \cdot a_{lj} \right|}{\max\limits_{j} \left| w_j \cdot a_{kj} - w_j \cdot a_{lj} \right|} \text{ with } k,l \in \{1,\ldots,n\} \wedge k \neq l\,.$$

Third, we build the *concordance dominance matrix* $\mathbf{F} \in \mathbb{R}^{n \times n}$ and the *discordance dominance matrix* $\mathbf{G} \in \mathbb{R}^{n \times n}$. To assess the elements for both matrices, we need to specify clear threshold values. In case of the concordance dominance matrix, the mean strength of concordance $\overline{con}$ may serve this purpose and filter insignificant outranking relations [ZiGu91, 210–211]. The elements f_{kl} of the concordance dominance matrix **F** are then estimated by

$$f_{kl} = \begin{cases} 1 & con_{kl} \geq \overline{con} \\ 0 & con_{kl} < \overline{con} \end{cases} \qquad \text{with } \overline{con} = \sum_{\substack{k=1 \\ k \neq l}}^{n} \sum_{\substack{l=1 \\ l \neq k}}^{n} \frac{con_{kl}}{n \cdot (n-1)}\,.$$

Similarly, the elements g_{kl} of the discordance dominance matrix **G** are found by comparing the discordance indices dis_{kl} to a discordance threshold value, for which we analogously assume the mean strength of discordance $\overline{dis}$ [ZiGu91, 211]:

$$g_{kl} = \begin{cases} 1 & dis_{kl} \leq \overline{dis} \\ 0 & dis_{kl} > \overline{dis} \end{cases} \qquad \text{with } \overline{dis} = \sum_{\substack{k=1 \\ k \neq l}}^{n} \sum_{\substack{l=1 \\ l \neq k}}^{n} \frac{dis_{kl}}{n \cdot (n-1)}\,.$$

Upon reflection of the two matrices **F** and **G**, we can see for which alternatives evidence for an outranking relationship is found: whenever zero is the pivotal element of comparing a “row alternative” to a “column alternative”, the outranking relationship is rejected, whenever a one is found, it is confirmed [ZiGu91, 211].

Afterwards, in a forth step, we aggregate the two matrices into a *dominance matrix*

$\mathbf{E} \in \mathbb{R}^{n \times n}$ [ZiGu91, 211]. The matrix elements e_{kl} are formally computed by

$$e_{kl} = f_{kl} \cdot g_{kl} \ \forall \ k,l \in \{1,\ldots,n\} \wedge k \neq l \ .$$

Fifth and finally, we eliminate all "dominated" alternatives *l* for which there is an alternative *k* that satisfies

$$\exists e_{kl} = 1 \ \forall \ k,l \in \{1,\ldots,n\} \wedge k \neq l \, .$$

The remaining dominating alternatives are regarded as incomparable and comprise the so-called *kernel* [BeSt02, 238–239], [Roy73, 195].

The *ELECTRE I* method relies heavily on the arbitrarily selected threshold values in the third step. It remains open whether the mean is a good guess or whether distinct vetoes should be specified by the DM. The robustness assumption can be rejected when thresholds are adjusted [ZiGu91, 219–220]. Recently the robustness of two other ELECTRE methods has also been questioned as ranks may appear to reverse [WaTr08, 55].

More importantly, all ELECTRE methods are non-compensative: Although we use weights, those do not represent trade-offs in the comparison process, but merely measure the strength of concordance in pairwise comparisons [BMP+00, 137]. In concrete applications, stakeholders will most likely distrust this interpretation of weights and will not appreciate the method intuitively [Stew92, 580].

4 Application of the Extended TOPSIS to the Scenario

4.1 Structure

This Section is concerned with describing the scenario and applying the selected MCDM method (Figure 31). We begin with a summary of the preceding two sections and join the results to establish a basis for detailed specifications of the scenario (Subsection 4.2). Then we describe the environment and the actors, detail their course of interaction, the offer attributes, and glance at the given preference information (Subsection 4.3). Farther, we define the extended TOPSIS method and apply the technique to a numerical example (Subsection 4.4). We close with having a glance at the insights of the application (Subsection 4.5).

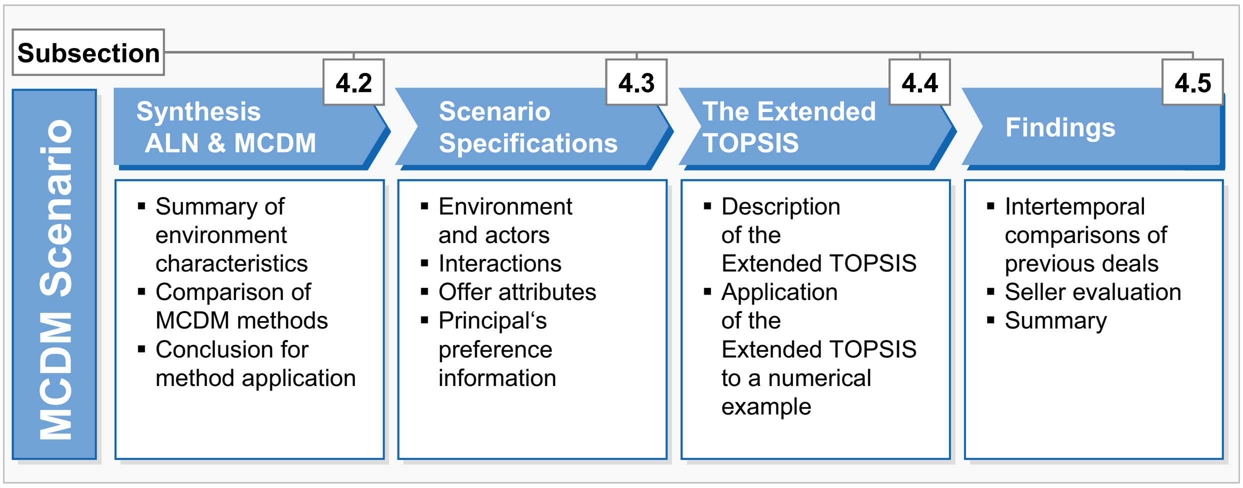

Figure 31: Outline of the 4th Section

4.2 A Synthesis of ALN and MCDM

4.2.1 Summary of Environment Characteristics

Several characteristics emerged from the analysis of the environment and the underlying paradigms in Section 2; they lead to the following eight implications for the construction of our scenario (Table 14). The degree of appropriateness of each MCDM method depends on the extent to which these prerequisites are satisfied.

Although up to this point we did not distinguish between buying and selling agents, our future explications will concentrate on the buyer. The inverse process for sellers is exempted from now on, since salient differences exist, e.g. in terms of commodities it is less likely that the seller will compare potential buyer candidates.

Table 14: Summary of scenario characteristics

Prerequisite	Implication	Reference (Subsection)
1. ALN is provider of storage capacity	The ALN represents a **virtual** storage system built by a set of linked up computer systems. Their owners trade with each other in a **competitive** manner.	**2.2**; **2.3.2**
2. Reasoning and learning	Cognitive agents carry out **reasoning** processes before deciding. This requires the individual **adaptation** of the agent's **preference** function.	**2.3.1.2**; **2.3.1.1**
3. Actors are DBAs	DBAs interact in the environment on **behalf of** their **human principals**.	**2.3.1.3**
4. Information transmission	Agents disseminate and gather information **voluntarily**.	**2.3.3**
5. Commodity trading	Object of interaction is the trade of a **commodity**, namely storage capacity, which is presumed to be non-distinguishable from individual sellers.	**2.4.1**
6. Price building in English auctions	Prices are set in an English auction, thus **price limits** have to be set.	**2.4.2.3**
7. Social reputation and image	Image and social reputation constitute two **differentiation dimensions** taken into consideration before deciding. Image and social reputation are weighted with a reliability measure reflecting the soundness of each value.	**2.5.2.3**
8. Multiple Criteria Decision Making	Buyers are confronted with seller's (possibly) **conflicting criteria** image, social reputation and current price. To balance these criteria, MCDM tools are necessary.	**2.6.3**

We keep this and the requirements listed above in mind and turn to a first description of the main process of trade in the scenario:

The DBA is supposed to buy storage capacity and as a registered participant of an electronic marketplace, the DBA is *able* to trade (*prerequisites 1* and *5)*. Before entering the market, the DBA has received initial instructions from his principal; the DBA obeys these orders and strives to develop over the course of time in the sense of his principal (*prerequisite 2* and *3*). While allowing different preferential structures of human beings, the principal's primary instructions have to include at least the preference function of the principal (*prerequisite 2*).

In the process of trading, the shopping agent seeks social reputation and image information about his potential partner and compares offers with the help of a yet unknown MCDM method (*prerequisites 4, 7* and *8*).

After each closing of a deal, the DBA reflects and memorizes the outcome, and sends feedback on his previous partner to the auctioneer (*prerequisites 4, 6 and 7*). The process is illustrated below (Figure 32).

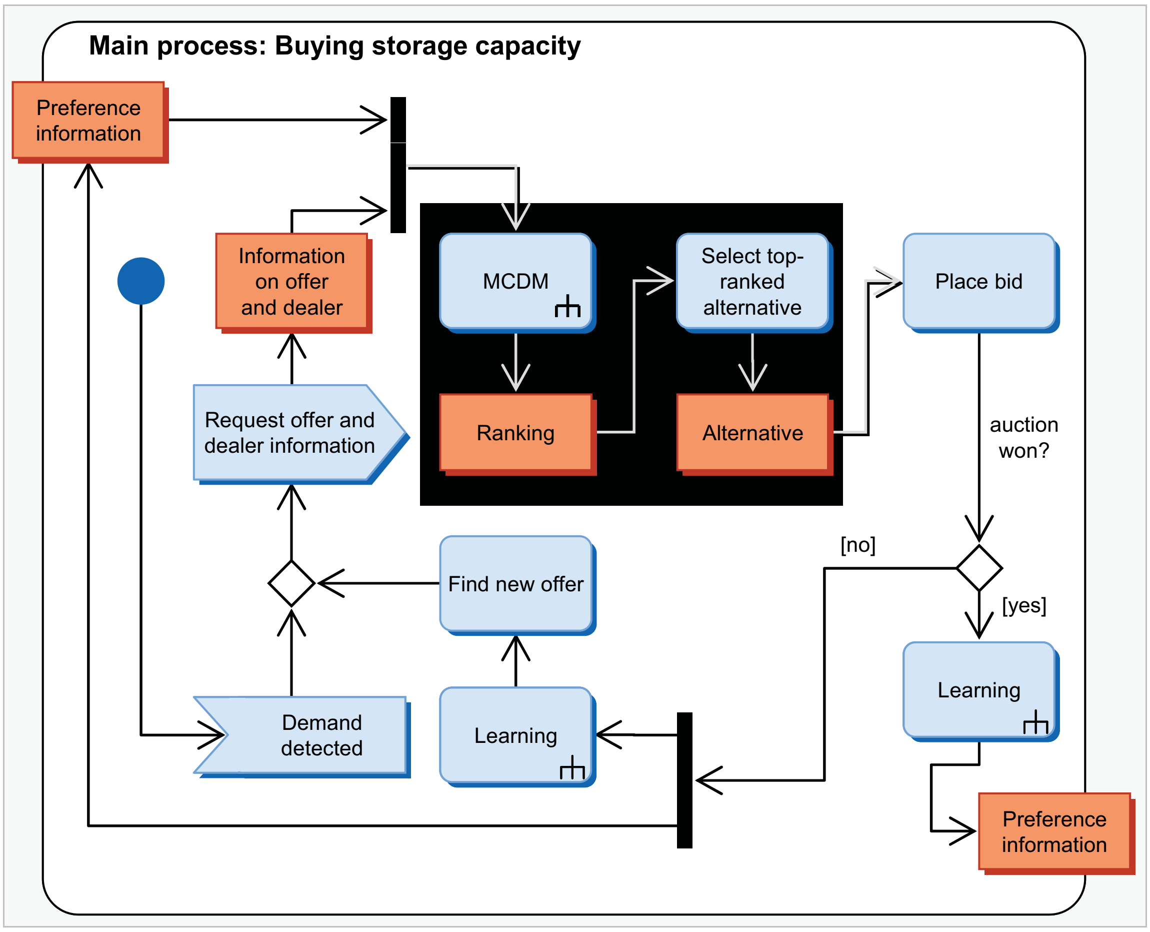

Figure 32: The main process of buying storage capacity and the MCDM blackbox

When presenting a bird's eye view of the just sketched main process, objects for discussion might arise at every step. Regarding many conditions as determined *ex ante*, our focus lies in shedding light on the "*MCDM black box*" of processing information, making a decision, and providing a decisive advice for bidding (Figure 32).

Concerning *prerequisite 6 and 8*, auction designs dealing with multiple attributes have been recently suggested [TWWZ06, pp.93–94], [Bich01, pp.140–142]. But in our case, reputation values are no attributes a seller can actively manipulate. Therefore we omit all such proposals in this work.

4.2.2 Comparison of MCDM Methods

Our objective for this Section has been the elaboration of an appropriate method for converting data of numerous alternatives into a specific recommendation. At this stage we compare the presented methodologies for MCDM and decide in favor of a particular method. This course of action is also called the *meta decision model* [Hann99, 6-3].

The design and the historical development of meta decision models is presented in detail in [Hann99]; for MADM methods, a dialogue-based advisory expert system has been developed in order to incorporate user preferences in the model selection [Ozer92, 166–168].

We rule out infeasible approaches as proposed in Ozernoy's subsequent elimination of methods and the decision tree of choice rules suggested by Hwang and Yoon as well as MacCrimmon [Ozer88, 248–249], [HwYo81, 210–213], [Macc73, 36–40]. But prior, we consider the prospective scenario with its characteristics to derive prerequisites for selecting a method (cf. the summary in Subsection 4.2.1).

According to Easton, the selection of an appropriate MCDM method is liable to a set of *rules* including easy justification, reasonable effort, efficiency, provision for scales and units, and producing a satisfying result [East73, 666]. Bearing these criteria in mind, we structure our prerequisites with respect to the process flow, and make use of the Conjunctive approach (i.e. a *rule*) to exclude inadequate methods (Figure 33). First, we take a closer look at the *input* side with subject-related and object-related prerequisites[4]:

Regarding the subject-related prerequisites, the owner instructs the buying agent with preference information. This information reflects an individual, underlying utility function of the principal (without explicitly formalizing this unknown function). From the subject's point of view, preference information has to represent the relevance of each criterion, either in comparison to others, or in terms of minimum (maximum) requirements, i.e. aspiration levels. When comparative relevance for criteria is regarded, we apply weights to criteria outcome (cf. Subsection 3.2.3), and when thresholds are specified, we refer to aspiration levels (as in satisficing).

---

4 We do not divide the prerequisites in terms of subjective and objective matters, since criteria values depend partly on the object (price) and on the buyer (image).

Referring to the Section 2, we now turn to the object-related prerequisites, assuming the agent is buying a commodity. This means except for the *price*, offers cannot be differentiated (service measures like terms of delivery are omitted). But beyond product characteristics, the agent considers *image* and *social reputation* of a seller. Thus, three criteria are subject of the decision problem. More important, on a super large-scaled marketplace, it is very likely that no image but only a social reputation value is available, thus we need a *compensatory* method which allows trade-offs between criteria (cf. 2.5.2.1). To allow compensation, we assume the relations between the three criteria are independent in our simplified case. If that holds for price and reputation in everyday life is questionable – and to be strict, in the sense of ReGreT, image exerts a slight influence on social reputation. Due to the tremendous number of market participants, we assume this effect to be insignificantly small. Otherwise all methods based on additive utility assumptions would have to be disregarded.

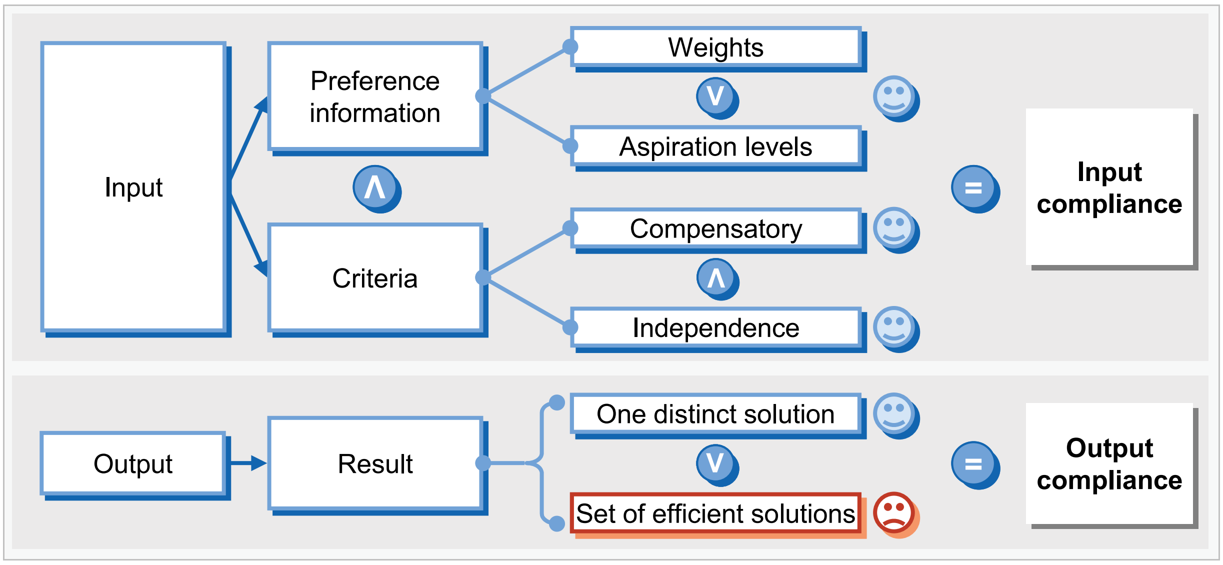

Figure 33: Prerequisites for the appropriate MCDM method

Second, we address the *output* side of the MCDM method:

The result of the decision-making process has to be a specific recommendation in terms of one offer to bid for, i.e. *non-interactivity* from the DM's point of view is essential. MCDM approaches which merely generate a set of efficient solutions are of little help, since they require interaction with the principal to continue bidding. Those interactions are to be avoided, as they delay the fulfillment process and thus impede the system efficiency (for the facets of interactivity in terms of *interactive MCDM approaches* see [Stew99, 10-2–10-3]).

Now as we have compiled all the prerequisites, we need to confront them with the features of the discussed methods. To facilitate the comparison, we listed all techniques below (Table 16, 69). The dimensions of information given in the overview are explained in the table before (Table 15).

Table 15: Dimensions of the comparison table

Method		
	Name or acronym of the method as given in this work	
Type		
	MADM	MADM method
	MODM	MODM method
	Outranking	Outranking method (Decision aid)
Set of options		
	Size of the set of alternatives	
	Finite	Bounded to a countable number
	Infinite	Unrestrained and not-countable large
Scale level (Scale level required)		
	Minimum level at which given informations have to be scaled	
Norm (Normalization)		
	Yes/ No	Normalized information required
Comp (Compensatory)		
	Yes/ No	Rather compensatory
Pref (Preference modeling)		
	Yes/ No	Known preferences of the DM modeled in the method
Output (Output of the MCDM method)		
	0	Rather a single solution; non-interactive
	1	Single solution or set of efficient alternatives equally possible
	2	Rather a set of efficient alternatives
Supplementary information		
	In addition to the decision matrix needed information	
Set of supplementary information		
	Extent to which supplementary information is needed	
Case		
	Yes/ No	Computed example provided in case study in Appendix B
Ref (Reference)		
	Points to the Subsection of the method	

Table 16: Comparison of MCDM methods

Method	Type	Set of options	Scale level	Norm	Comp	Pref	Output	Supplementary information	Set of supplementary information	Case	Ref
Dominance	MADM	Finite	Ordinal	No	No	No	2	-	-	Yes	3.3.2.2
Maximin/ Maximax	MADM	Finite	Ordinal	Yes	No	No	0	-	-	Yes	3.3.2.3
Satisficing (Conjunctive)	MADM	Finite	Ordinal	No	No	Yes	2	Aspiration levels	*m*	Yes	3.3.3
Satisficing (Disjunctive)	MADM	Finite	Ordinal	No	Yes	Yes	2	Aspiration levels	*m*	No	3.3.3
Lexicographic Methods	MADM	Finite	Nominal	No	No	Yes	1	Attribute order of relevance	*m*	Yes	3.3.4.2
EbA	MADM	Finite	Ordinal	No	No	No	1	Standards	*m*	Yes	3.3.4.3
SAW	MADM	Finite	Cardinal	Yes	Yes	Yes	0	Weights for attributes; values derived from outcomes	*m*	Yes	3.3.5.2
WPM	MADM	Finite	Cardinal	No	Yes	Yes	0	Weights for attributes; outcomes ≥ 1	*m*	Yes	3.3.5.2
AHP	MADM	Finite	Cardinal	Yes	Yes	Yes	0	Relative importance of criteria and alternatives with respect to parental nodes	at least $[m \times (m\text{-}1) + m \times n \times (n\text{-}1)] \div 2$ *(three-level hierarchy)*[a]	Yes	3.3.5.3
TOPSIS	MADM	Finite	Cardinal	Yes[b]	Yes	Yes	0	Weights for attributes	*m*	Yes	3.3.5.4
Goal Programming	MODM	Infinite	Cardinal	Yes	Yes	Yes	1	Weights for attributes; aspiration levels	*m*	No	3.4.2
ELECTRE (I)	Outranking	Finite	Ordinal	Yes[b]	No	Yes	2	Weights for attributes	*m*	Yes	3.5.2

a May also be derived from $(m \times n)$ given values

b Vector normalization by developers recommended

4.2.3 Conclusion for Method Application

With the help of the comparison table and the input and output prerequisites, we can depict the discussed methods on a two-axis chart. The method for our scenario should be one of the equally suitable four in the upper right quarter (Figure 34).

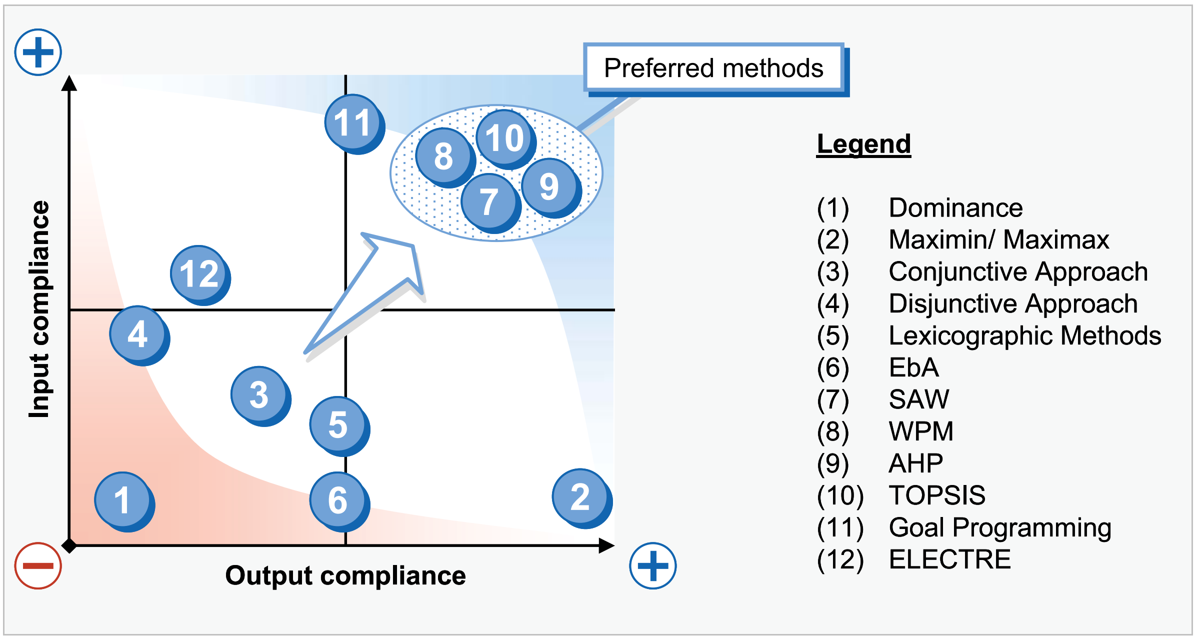

Figure 34: Classification of MCDM methods in the light of the scenario

At this stage, we bestow consideration upon the complexity of each method in a nutshell: The SAW method and WPM are probably the most straightforward methods and constitute no insurmountable obstacle in determining aggregates from $m \times n$ outcomes. The TOPSIS comprises eliciting minimum and maximum values for all m criteria from the given set of n alternatives, as well as calculating n distance vectors. These $m \times n$ computations are manageable as well, even for a huge set of alternatives.

A sharp contrast is the AHP – with an increasing number of n alternatives for m criteria, the number of pairwise comparison matrices, which have to be processed, with each matrix subject to $\left[n(n-1)\right] \div 2$ evaluations, soars by the factor of m, means incrementally about $m \times n^2$ evaluations (e.g. 100 alternatives and three criteria already need 14.853 comparisons, cf. p. 51) [Brug04, 310]. Hence, we eliminate the AHP from our list.

Concerning the remaining three approaches, we choose the TOPSIS method for one reason: If we store the current ideal solution vectors in a repository database, we are able to trace the experiences our agent has made and the development he underwent. We will explicate this in more detail in Subsection 4.4.1.

Apart from our decision, two other practices are to be considered when solving a multiple criteria decision problem:

On the one hand, we could build a system of rules, which filters insufficient alternatives stepwise, e.g. by combining Conjunctive and Disjunctive approaches. Such a system would be equivalent to the way in which we decided above on the MCDM method. That means, we would equip the agent with a set of rules consisting of ranges or bounds for criteria values for which we consider an alternative to be satisfying [Ozer88, 246–247]. Even though the agent would not seek the best, but merely satisfying solution, this procedure may be preferable when extensive computations jeopardize the system's stability or when processing power becomes a bottleneck; we assume this does not apply to the case of our future scenario.

On the other hand, we could employ simultaneously different MCDM methods, let each one determine the optimal solution, aggregate the ranked sets and synthesize them afterwards [HwYo81, 214]. But especially when dealing with a large number of criteria or alternatives, this may seriously threaten a system's overall performance.

We take note of both ideas here, but do not contemplate the implementation for the above stated reasons.

4.3 Scenario Specifications

4.3.1 Environment and Actors

Our ALN consists of a very large number of individual computer systems, each one offering limited storage capacity for hire on payment of a fee. Every computer system belongs to a principal and is represented by an agent, which at a particular time is either offering or seeking storage capacity. A central institution collects offers from sellers, enriches them with reputation information and forwards them to buyers. Because this intermediary also provides access to the network, we call it the *hub* (Figure 35).

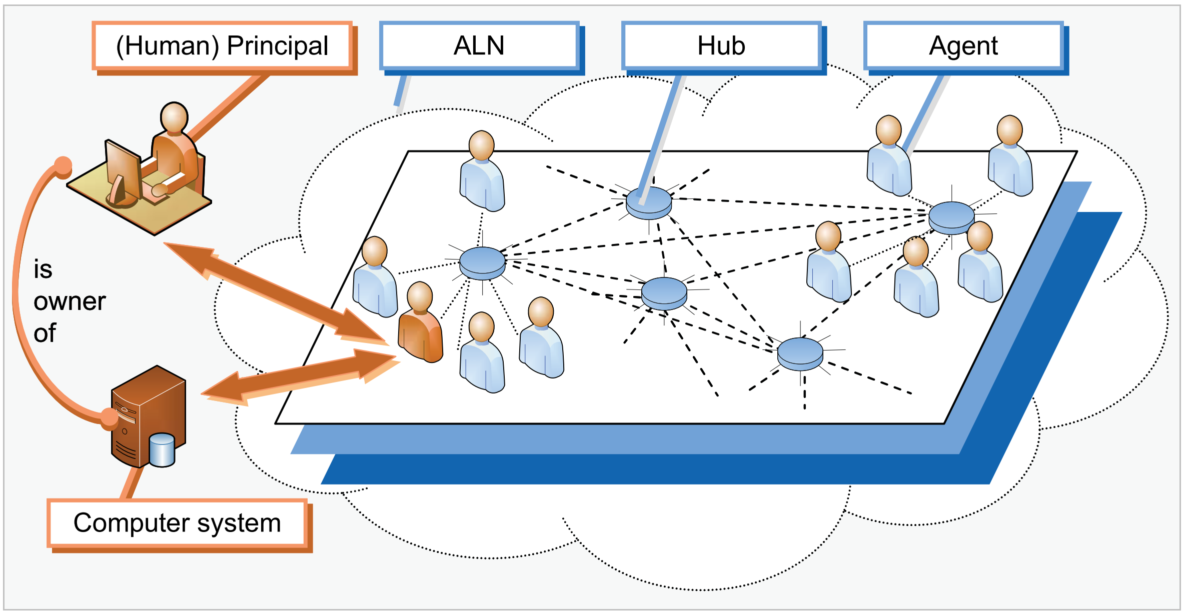

Figure 35: Scheme of the scenario

4.3.2 Interaction between Actors

On the basis of the already illustrated main process in Section 2 (Figure 32, p. 66), we explain in detail the interaction of buyer, seller and hub within the ALN in the following paragraphs (for a UML *sequence diagram* see Figure 36):

Whenever an agent receives a demand note for hard disk space from his connected system, he sends out a request for offers to the hub. The hub collects current offers from his offer database and searches his reputation databases for impression entries corresponding with the current sellers; if entries are available, reputation is calculated and attached to the offer information. Then the hub forwards the information package to the requesting agent.

After the buyer receives the current available offers from the hub, he browses his own image database for previous experiences with the present sellers and if available, adds the image value to the corresponding offer. With this information, the MCDM procedure is carried out, a best alternative is determined and the buyer submits his price quote to the seller.

When negotiations are successfully finished, the transaction is fulfilled by transferring payment and accessing the hard disk partition for storing data (this step is subsumed under the term *delivery*).

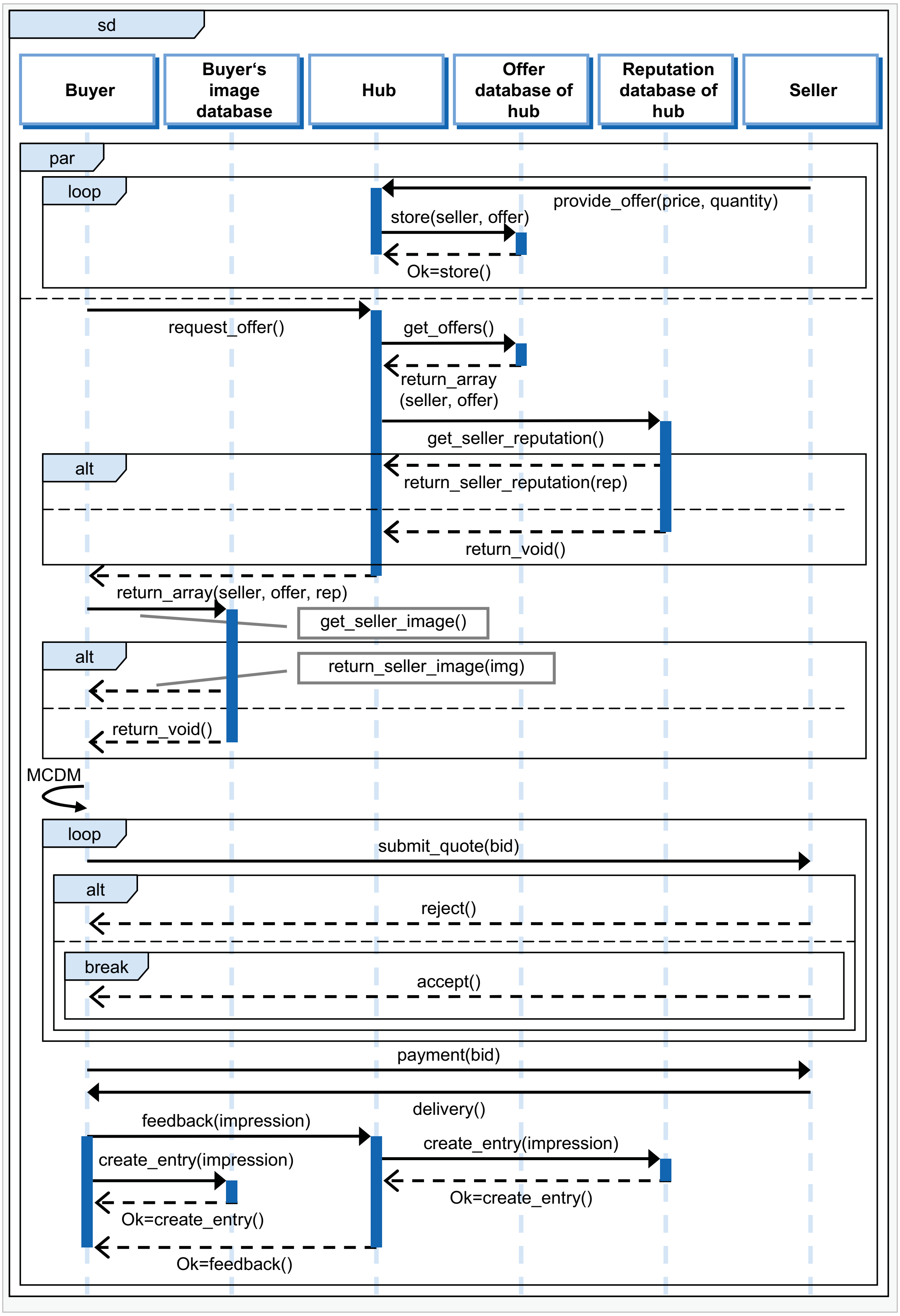

Figure 36: Interaction within the ALN

Afterwards, the buyer sends feedback in terms of an impression tuple to the hub, which stores this information in the associated reputation databases. The buyer simultaneously adds impressions to his image database for future consultation.

While prospective buyers communicate with the hub, the offer database is fed continuously by selling agents, as long as capacity is for sale.

4.3.3 Offer Attributes

The three distinguishing attributes associated with an offer are price, social reputation and image (Table 17). The buying agent strives to maximize all of these attributes, except for the price.

Table 17: Offer attributes

Attribute	Symbol	Goal	Source	Domain	Special case
Price of offer *i*	PR_i	Minimize	Seller (through hub)	$PR_i \in [0;\infty[$	
Social reputation of seller of offer *i*	SR_i	Maximize	Hub's SDB and IDB	$SR_i \in [0;1]$	$\nexists SR_i \in [0;1] \Rightarrow SR_i = 0.5$
Image of seller of offer *i*	IM_i	Maximize	Buyer's ODB	$IM_i \in [0;1]$	$\nexists SR_i \in [0;1] \Rightarrow SR_i = 0.5$

The price is initially set by the seller and varies with the number of offers and request from agents due to the nature of the price mechanism, the English auction: a surging demand leads to rising prices, a dropping one cuts prices (cf. Subsection 2.4.2.3, p. 15). The posted price relates always to a specified amount of capacity (one GB) and period for which the capacity is provided (e.g. one month). This unit of "price per GB per month" is assumed to be mutually accepted and fixed – no variances are possible and if capacity is needed for less than a month or less than a GB is required, the price will still have to be paid for the full unit and the complete term. We assume that a price is always positive and that there is no upper bound.

Social reputation is no mandatory information: in case no feedback on the seller has been provided yet, no reputation value exists. The sources for reputation information are the SDB and the IDB, and both databases are locally maintained by their parent hub (cf. Subsection 2.5.2.3, p. 22). The hub automatically accesses his databases, retrieves available information and calculates social reputation. The resulting value is normalized on an interval from zero to one with a value of one indicating the best judgment of one's reputation, whereas values close to zero represent very bad reputation.

Image is similar to social reputation in almost all terms except for its origin. The source of image is the buyer's ODB with impression entries from previous encounters with sellers (cf. Subsection 2.5.2.3, p. 21). Although the buyer controls the computation of image values, we do not examine different levers for manipulating this process. Image is also provided on a scale from zero to one, with the value of one being a sign for exceptionally positive previous encounters, and the value of zero meaning the seller is least trustworthy.

Since an agent has access to exactly *one* hub, he can neither monitor a *current overall marketprice* nor compute a market equilibrium [Vari06, 572]. The only key figure one may compute are local mean or deviation measures of the given offers, but these figures are not needed here. If an image or social reputation value is not provided, we put the scale mean of 0.5 in as a substitute to avoid unwanted discrimination.

4.3.4 Principal's Preference Information

The preference information required for running the scenario comprises a weight vector with values for each attribute. At the beginning the principal is interrogated to elicit his preference structure on price, image and social reputation.

The interview produces a criteria comparison table (cf. Subsection 3.2.3) and calculates the following results (Table 18):

Table 18: Weight vector

	PR	***IM***	***SR***	**Sum**	**Weight**
PR	1	1/2	3/4	2.25	w_{PR} = 0.23 = **23 %**
IM	2	1	3/2	4.5	w_{IM} = 0.46 = **46 %**
SR	4/3	2/3	1	3	w_{SR} = 0.31 = **31 %**
			Sum	9.75	$\sum w_j = 100\ \%$

During our experiment we assume these weights are constant and are not subject to manipulation, neither by the principal nor by the agent.

4.4 The Extended TOPSIS

4.4.1 Description of the Technique

The TOPSIS creates every time two virtual bounds against which all alternatives are ranked (cf. Subsection 3.3.5.4, p. 53). This feature is helpful when tracking past selections and comparing them in the course of time. The two bounds incorporate the extreme values for attributes of all received alternatives so far, thus, it serves as a "packed memory" one may consult when ranking the previously selected alternatives.

A ranking of selected alternatives (a "best-of-the-best list") allows assessments of the past performance of the buyer agent, e.g. analyzing whether specific hubs provide frequently malevolent sellers or specific periods when demanded prices are unusually low. This cannot be achieved easily by applying MCDM methods such as the WPM or the SAW method because those methods mask all but their synthesized score value (cf. Subsection 3.3.5.2, p. 45).

We propose an *Extended TOPSIS* (xTOPSIS) approach here, which computes the two bounds *over the course of time* instead of resetting the ideal solution vectors after every instance. This means, after their first construction, the two vectors with the ideal solution are reverted into their original values and added to the set of alternatives every run before carrying out the TOPSIS procedure (Figure 37). We call these two extreme points *negative and positive ideal vector*.

In order to apply this line of action we replace the vector normalization with the linear one as accomplished before by [YuC003, 1000], [Chu02, 695]. The linear transformation requires merely two extreme values for scaling – and these parameters are given at any time by the two ideal vectors.

Furthermore, we need to store three vectors after every run: First of all, the positive and negative ideal vectors are saved in a database, namely the *Ideal Vector Database* (IVD). Besides we establish a *Partner Database* (PD) consisting of all offers the agent successfully seized. With the help of these two storages, we can align attribute values of alternatives on a single scale and compare them to each other.

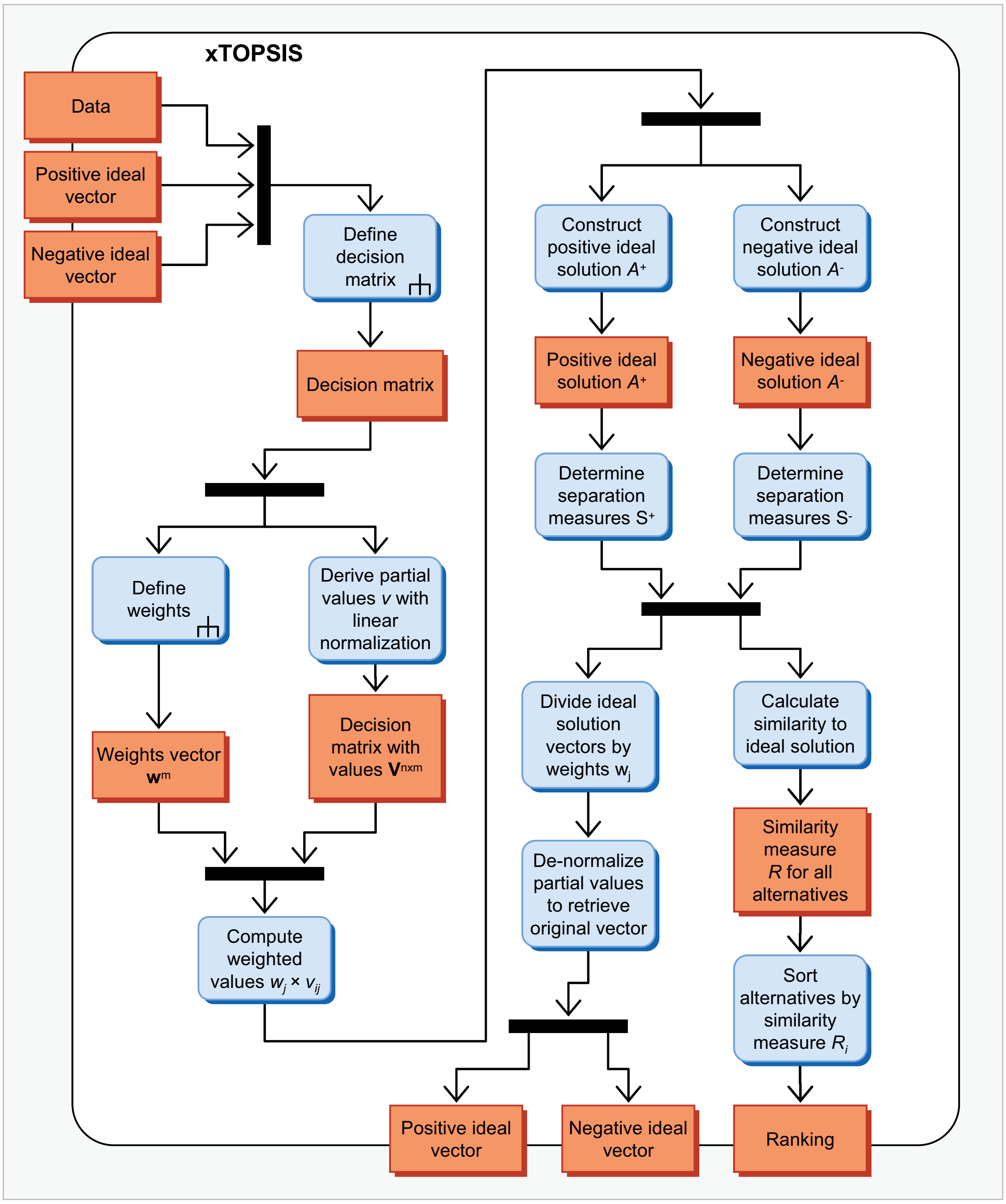

Figure 37: Process of the extended TOPSIS

4.4.2 Application of the xTOPSIS: A Numerical Example

We run the main process of buying storage for three times and analyze the results. Basis for the main process is the draft of Section 2 (cf. Figure 32, p. 66) in which we replace the MCDM subprocess with the xTOPSIS method (a slightly updated version of the main process is attached in Appendix A 3, p. 107).

In the first round, the following set of alternatives is given, with best values highlighted in blue and poorest ones in red (Table 19):

Table 19: Decision matrix of the 1st round

Alternative	*PR*	*IM*	*SR*
A1.0	0.312	0.25	0.47
A1.1	0.198	0.45	0.21
A1.2	0.446	0.24	0.65
A1.3	0.390	0.64	0.20
A1.4	0.494	0.65	0.34
A1.5	0.284	0.18	0.59
A1.6	0.893	0.57	0.77
A1.7	0.430	0.73	0.13
A1.8	0.893	0.9	0.41
A1.9	0.042	0.43	0.21

We normalize the attribute values using the linear transformation and multiply them with the weights specified above, e.g. the weighted normalized value for the price of alternative A1.1 is

$$(\text{Normalized price value}) \cdot \text{Weight}_{\text{Price}} = \frac{a_j^{\max} - a_{ij}}{a_j^{\max} - a_j^{\min}} \cdot w_j = \frac{0.893 - 0.198}{0.893 - 0.042} \cdot 0.23 \approx 0.188\,.$$

Then we get the following result (Table 20):

Table 20: Weighted normalized decision matrix of the 1st round

Alternative	*PR*	*IM*	*SR*
A1.0	0.157	0.045	0.165
A1.1	0.188	0.173	0.039
A1.2	0.121	0.038	0.252
A1.3	0.136	0.294	0.034
A1.4	0.108	0.3	0.102
A1.5	0.165	0	0.223
A1.6	0	0.249	0.31
A1.7	0.125	0.351	0
A1.8	0	0.46	0.136
A1.9	0.23	0.16	0.039

We can read off the positive and the negative ideal solution from the weighted normalized decision matrix: the positive ideal solution A_1^+ is described by the vector (0.23; 0.46; 0.31) and the negative ideal solution A_1^- is (0; 0; 0).

The similarity to ideal solution of an alternative is computed by the fraction of the closeness to A_1^- and A_1^+, presented below for alternative A1.5. With

$$S_{A1.5}^{+} = \sqrt{(0.165-0.23)^2+(0-0.46)^2+(0.223-0.31)^2} \approx 0.4726$$ and

$$S_{A1.5}^{-} = \sqrt{(0.165-0)^2+(0-0)^2+(0.223-0)^2} \approx 0.2774,$$ the relative closeness is

$$R_{A1.5} = \frac{S_{A1.5}^{-}}{S_{A1.5}^{+}+S_{A1.5}^{-}} = \frac{0.2774}{0.4726+0.2774} \approx 0.3698\,.$$

We estimate these figures for all alternatives and arrange the alternatives in a descending order by their relative closeness (Table 21):

Table 21: Closeness values and ranking for the 1st round

Alternative	S_1^+	S_1^-	R_1	Rank
A1.0	0.4456	0.2322	0.3425	10
A1.1	0.397	0.2584	0.3943	7
A1.2	0.4397	0.2821	0.3908	8
A1.3	0.3355	0.3257	0.4926	5
A1.4	0.2894	0.3348	0.5363	3
A1.5	0.4726	0.2774	0.3698	9
A1.6	0.3121	0.3976	0.5602	2
A1.7	0.345	0.3726	0.5192	4
A1.8	0.2884	0.4797	0.6245	1
A1.9	0.4043	0.2829	0.4117	6

Our agent is now advised to bid on offer A1.8, which excels in the set of the first run and our assumption is that he wins the respective auction. So far, the TOPSIS method is unaltered.

But now we are storing the original values of alternative A1.8 in the PD and the ideal vectors in the IVD. We can either retrieve the values from the weighted normalized decision matrix or extract them directly from the initial decision matrix (Table 19): the vector of the positive ideal is (0.042; 0.9; 0.77), the one of the negative ideal is (0.893; 0.18; 0.13).

In the second round, we add the two ideal vectors to the set of alternatives forwarded from the hub (Table 22):

Table 22: Decision matrix of the 2nd round

Alternative	***PR***	***IM***	***SR***
A2.0	0.525	0.62	0.19
A2.1	0.478	0.25	0.63
A2.2	0.311	0.03	0.48
A2.3	0.605	0.3	0.96
A2.4	0.134	0.29	0.61
A2.5	0.687	0.91	0.15
A2.6	0.296	0.18	0.42
A2.7	0.258	0.49	0.37
A2.8	0.272	0.43	0.56
A2.9	0.597	0.11	0.85
A_1^- (from previous round)	0.893	0.18	0.13
A_1^+(from previous round)	0.042	0.9	0.77

We can see image values in the new set of alternatives lying beyond our current boundaries, and the same applies to social reputation values excelling the latest upper bound. Hence, these new extremes overwrite the respective values in the ideal vectors. During normalization, the maximum and minimum values are taken from the ideal vector, e.g. for the social reputation of alternative A2.5 we compute

$$(\text{Normalized social reputation value}) = \frac{a_{ij} - a_j^{\min}}{a_j^{\max} - a_j^{\min}} = \frac{0.15 - 0.13}{0.96 - 0.13} \approx 0.0241\,.$$

The weighted normalized decision matrix with closeness and similarity measures as well as ranks is depicted below; the ideal vectors are left out, since they play no role for deciding. This round, our agent is supposed to pick alternative 2.5 for bidding now and we assume he successfully strikes the bargain (Table 23). Then we update again the ideal vectors and store them in the BD, while alternative 2.5 is treasured in the PD.

Table 23: Weighted normalized decision matrix, closeness values and ranks of the 2nd round

Alternative	*PR*	*IM*	*SR*	S_2^+	S_2^-	R_2	Rank
A2.0	0.099	0.308	0.022	0.351	0.3243	0.4802	5
A2.1	0.112	0.115	0.187	0.3848	0.2465	0.3904	7
A2.2	0.157	0	0.131	0.499	0.2045	0.2907	10
A2.3	0.078	0.141	0.31	0.3534	0.3494	0.4972	3
A2.4	0.205	0.136	0.179	0.3504	0.3042	0.4648	6
A2.5	0.056	0.46	0.007	0.3494	0.4634	0.5701	1
A2.6	0.161	0.078	0.108	0.4376	0.209	0.3232	9
A2.7	0.172	0.24	0.09	0.3165	0.3087	0.4938	4
A2.8	0.168	0.209	0.161	0.2984	0.3128	0.5118	2
A2.9	0.08	0.042	0.269	0.446	0.2838	0.3889	8

The set of alternatives in the third round is once more complemented by the current ideal vectors. This time we skip depicting the step of normalizing and weighting, and attach instead closeness and similarity measures with ranks directly (Table 24).

Table 24: Weighted normalized decision matrix, closeness values and ranks of the 3rd round

Alternative	*PR*	*IM*	*SR*	S_3^+	S_3^-	R_3	Rank
A3.0	0.388	0.4	0.03	0.4146	0.2362	0.3629	9
A3.1	0.455	0.43	0.78	0.2807	0.3476	0.5532	4
A3.2	0.373	0.54	0.01	0.3761	0.3015	0.4449	6
A3.3	0.663	0.76	0.38	0.264	0.4056	0.6058	2
A3.4	0.902	0.63	0.71	0.2845	0.388	0.577	3
A3.5	0.215	0.29	0.29	0.394	0.2447	0.3832	8
A3.6	0.511	0.22	0.74	0.3891	0.278	0.4167	7
A3.7	0.745	0.83	0.37	0.2727	0.4361	0.6153	1
A3.8	0.246	0.48	0.39	0.2972	0.3176	0.5166	5
A3.9	0.035	0.08	0.31	0.483	0.2514	0.3423	10
A_2^- (from previous round)	0.893	0.03	0.13				
A_2^+(from previous round)	0.042	0.91	0.96				

This time our agent is recommended to seize offer A3.7, and after closing the deal the original values are again saved in the PD. We also update the ideal vectors and copy the values to our IVD.

4.5 Findings from the Scenario Application

4.5.1 Intertemporal Comparison of Reached Agreements

Given the results from our previous example, a main advantage of the xTOPSIS approach is the ability to compare the quality of offers from different rounds.

After three rounds, our favored alternative A3.7 had a similarity value R_3 of 0.6153. We cannot contrast this value with the ones of the prime offers A1.8 (R_1=0.6245) or A2.5 (R_2=0.5701), because those values were calculated from differently scaled decision matrices. But since we stored the original values in the PD, we can scale alternatives A2.5 and A1.8 with our current positive (0.035; 0,91; 0,96) and negative ideal vectors (0.902; 0.03; 0.01). Then we retrieve

$$R_3\left(A1.8\right) = 0.6201 \qquad \text{and} \qquad R_3\left(A2.5\right) = 0.5959\,.$$

Alternative A1.8 becomes less favorable, while A2.5 rises in similarity to ideal solution? Reason for this development is the readjustment of scales and the relative placement of the alternatives before:

The impact of decreasing the lower bound of social reputation from 0.013 to 0.01 increases the nominator of the linear transformation and improves the relative position of alternative A2.5, which is exceptionally weak on social reputation. A1.8 is also affected by the change of bounds of social reputation – but in contrast to A2.5, the social reputation of alternative A1.8 became less attractive with the appearance of alternative A2.3, which set a new benchmark for the good name of a trader.

With a soaring number of entries in the partner database, more precise statements can be given about the quality of decisions made by the agent. Maintaining a database with reference values for future analysis is an invaluable asset for any agent as it provides key figures for automatic learning and self-adjustments.

For example, the agent may derive aspiration levels for all attributes from his experiences and withdraw all offers if none satisfies these requirements. After withdrawing several times the agent may autonomously decide to switch the hub and reconnect, or demand from the accessed hub forwarding his request for offers to different hubs.

4.5.2 Seller Evaluation

Seller evaluation is *not* automated in the process of the scenario. The quality of the storage provided cannot be determined by the buying agent, thus the principal is currently supposed to interact with the ALN and provide a feedback for the individual and the collective memory (the ODB and the current hub's IDB and SDB).

At this stage, the interactivity requirement is a bottleneck for large-scale applications since it impeds the process (cf. p. 68). To avoid this, we suggest the implementation of a yet unspecified automatism for evaluations.

4.5.3 Summary

Synthesizing the result from the comparison of eleven MCDM approaches with the prerequisites of the environment has led to three possible options: SAW, WPM and TOPSIS. We have chosen the latter since we saw the chance to derive additional benefit from the provision of extreme vectors compared to plain score values. Instead of estimating new reference vectors for each buying request, we store all references in a repository and adapt the two current ideal solutions during each run.

Thus, we can judge all alternatives by two dynamic reference vectors, and we determine the value of an offer not merely at a certain time, but also over several periods. With regard to this extension we have baptized the approach xTOPSIS.

The method is scalable and suitable for the given premises, and thus practical for large-scale analysis. Moreover, it provides an interface for monitoring the quality of past transactions as it creates a set of two vectors per transaction, which can be either used in overarching research on system performance or become subject of trade as well.

A drawback worth noting is the missing implementation of automated outcome evaluation. Since this problem is beyond our objective of defining a suitable MCDM method, we have not examined possible solutions.

5 Conclusion

5.1 Results

We have examined decision-making in ALN and concentrated on the case of processing reputation information during the purchase of goods. To automate the reasoning process of agents before selecting a supplier, we have analyzed the environment and extracted aspects of relevance for a suitable MCDM method.

The primary objective of this work was the elaboration of a suitable decision-making method for the simulation testbed of the eRep project. We deduced an approach called xTOPSIS from the prerequisites of the testbed, elaborated the foundations and presented a numerical example to illustrate the process. Thus the objective has been achieved.

In view of the secondary objectives we are able to answer the questions

- whether the chosen decision-making method can be applied to the trade of services and complex goods,
- which assumptions of the scenario impede transferring the results to human environments, and
- whether valuable added benefits can be drawn from the used method.

<u>Trading Services</u>

Shifting from commodities to complex goods or services means a soaring number of distinguishing features, i.e. an increase of criteria. Thus the number of processing operations rises: on the one hand because of additional preference information the agent needs from the principal, and on the other hand because of the size of the information requested from the hub. For the xTOPSIS this implies growing IVD and PD repositories and a growing number of computations.

Technically, the xTOPSIS is able to deal with the requirements of service procurement, but practically, one may question whether the TOPSIS philosophy is suitable for service procurement: In contrast to reputation, suppliers may be in the position of adjusting services attributes or balancing weaknesses in negotiation processes. Upon revealing a value function, buyers and seller are able to engage in multiattribute auction mechanisms which may be more helpful in this case [Bich01, 140–144].

Impeding Assumptions

During our elaboration several concessions had to be made in order to allow an efficient scenario modeling. Among those, the four aspects below seem most critical when it comes to transferring the results from the project to real life situations.

Although the purpose of this work has never been imposing a formal mechanism on real life social structures, when planing to establish an appealing and plausible eCommerce governance environment, we have to remind ourselves to the fact that the consumers sitting in front of computer screens are (still) human beings.

1. *Constant weights*: We can hardly imagine human beings attribute the same relevance to criteria in the long run. People rather adapt constantly and change preferences upon experiences. If weights are to be parameterized, then an additional *Weights Database* would have to be implemented to trace the change of relative preferences. The same applies to any measure implemented for enabling automated seller evaluation.
2. *Learning*: Currently, neither the seller nor the buyer agent reflect on past actions and improve their behavior. Assuming an automated evaluation mechanism exists, the buyer is supposed to consider the outcome of his conduct and adapt to the results. One idea might be excluding specific hubs or periods which provided less valuable bargains. This would be equal to a human being avoiding particular shopping malls or opening hours in which she was previously not satisfied by her transaction.
3. *Voluntary information dissemination*: The ReGreT mechanism relies on provided feedback from customers to compute the social reputation value. It is questionable whether individuals provide word-of-mouth for free, assuming transaction cost are inevitable. For example, one may consider implementing a deposit for retrieved reputation information, which is returned upon submitting feedback, or a market mechanism encouraging individuals to trade honest feedback.
4. *Additive value function*: Additive partial value functions are inherent in the TOPSIS approaches. But even in the regarded scenario, the necessary precon-

dition of mutual independence between those functions is violated – social reputation is slightly influenced by the image of an agent, if he previously met the regarded seller. In everyday life interdependencies between attributes such as reputation and price are also very likely. One thought may be considering nonlinear value functions such as the multiplicative one of the WPM.

This list of four obstacles is by no means extensive, and the nature of models such as the ReGreT mechanism suggest sources of conflict at every stage of abstraction; we briefly refer to the design of sociograms or the individual adaptations to the ontological dimension for calculating trust (cf. Subsection 2.5.2.3, p. 22).

Added benefits

Thanks to retaining previous ideal vectors (in the IVD) and seized offers (in the PD), the xTOPSIS allows intertemporal comparisons of reached agreements and ideal solutions. This means, for one thing we can analyze time series of temporary offer markets, for another one we can observe the performance of our agent.

The ideal vectors embody certain market states, since they comprise the extreme values of all alternatives on the market. Assuming time stamps and identity of the connecting hub are available as well, the data from the IVD can provide grounds for metrics such as average offer quality or correlation between price and reputation (in relation to periods or hubs). It furthermore allows enhancements for the reasoning process of an agent, e.g. computing thresholds, aspiration levels, or reservation values in reference to the previously encountered markets. If a threshold is not reached, the agent can be instructed to react with sanctions such as switching the hub or rejecting all offers.

The database with past encounters enables tracing the performance of an agent; scaling all previous deals with respect to one set of ideal vectors makes the results comparable. We can see which offers were above or below average, and if we connect the results with the evaluations from the ODB, we can try to define patterns of good and not-so-good suppliers, e.g. we may find out that reputation is a good predictor of quality for offers from certain hubs.

One can imagine the possibilities of analyzing past encounters and deriving predictions for future trading. Conducting data mining is possible with other value function methods as well, but the crucial disadvantage of SAW or WPM is the necessity to store *all* received offers with their attributes. In contrast, the TOPSIS approach supports our suggested extension in terms of efficiency.

5.2 Suggestions for Research and some Critical Annotations

During the development of our method several matters of interest arose, which we had to postpone until now. For the field of MCDM in ALNs, we reduce our suggestions for further research to the following issues:

- How can we delegate the process of evaluating outcomes to an agent?
- What constitutes the border between those goods for which we can apply MADM methods and those goods for which we need other approaches?
- To what extent are human beings willing to transfer responsibility to agents?

<u>Evaluating outcomes</u>

Currently, the whole subprocess of *learning* has not been specified. Learning itself is a problematic issue already mentioned above, but part of it includes the evaluation of outcomes.

Processing some rough information can be realized through comparing certain service level measures to specified, individual target values (such as medium access time, latency or access availability). But in terms of less easily quantifiable measures, how shall an agent derive an evaluation? Consider streaming a movie from a provider – though possible from a technical point, but hardly computable, how shall the buying agent estimate the quality of the movie? How shall he detect visual or acoustic differences *on time*, assuming all files use the same audio and video encoder?

This certainly asks for further research on mechanisms for delegating parts of the evaluation to agents.

<u>Limitations of MADM methods for comparable goods</u>

The elaborated method is sufficient for the straightforward comparison of commodity sellers. Beyond attribute-free goods, when it comes to more complex ones or services, information on the type of distinguishing features is necessary. Whereas the comparison of identical music files offered may come up with a few additional numerical attributes (such as the encoding bitrate), service providers offering PDF conversions may present a whole variety of encryption techniques, compression algorithms, or size restrictions.

Thus, further investigations are required to determine the limitations of MADM methods for comparing goods with multiple attributes.

Limits for transferring responsibility

Above the technical aspects, we need to ask ourselves in how far we *want* to delegate decision-making to autonomous agents. True, agents possess the ability to facilitate daily life by exchanging information and conducting trades of minor importance on behalf of the principals. But for privacy as well as self-determination matters, it is questionable whether individuals are willing to provide comprehensive information on their preference structure to their non-human *alter ego*, even if we take exhaustive security measures against abuse.

The individual concern for privacy protection leads to questions regarding already institutionalized rules [Seif86, 35–36]: The replication of preference structures and transaction histories severely violates individuals' privacy. Storing personal information in distributed repositories appears to interfere in several facets such as the right for privacy and self-determination with the *EC Directive on privacy and electronic communications*, e.g. Articles 5, 12 Directive 2002/58/EC [Euro02b], [Seif86, 38].

Moreover, assuming agents take on more or less *all* transactions between individuals, we may end up asking ourselves whether trading is not a common part of human behavior. Are we willing to forgo this habit? And can the human mind ever be appropriately represented by an autonomous device – or will we have to adapt our capacious human minds gradually to the limits of artificially empowered assistants [Lani96]?

If we agree on the ideas of digitalizing the human mind as well as forgoing the human habit of trading, the giving up of buying and selling provokes a decline of individual socializing [Seif86, 11]. In the extreme case the principals end up being socially isolated, transparent in their consume preferences and relying subconsciously on recommendations and orders of their agents. At the time masters and servants have exchanged their powers, we may remind ourselves to the *sorcerer's apprentice* from Goethe's famous poem, wishing we could drive out "the spirits that we called" [GoZe65, 103–109].

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Appendix

Appendix A

Appendix A 1: Classification categories and options (based on [SaSi05, 35–41])

Conceptual model		
	GT	Game-theory
	C	Cognitive
Information sources		
	DI	Direct interaction
	DO	Direct observation
	WI	Witness information
	SI	Sociological information
	P	Prejudice
Visibility		
	S	Subjective property
	G	Global property
Model's granularity		
	CD	Context dependent
	NCD	Noncontext dependent
Agent behavior assumptions		
	0	No cheating is considered
	1	Biased or hidden information possible
	2	Lying is recognized
Type of exchanged information		
	Yes / No	Boolean measures
Trust/reputation reliability measure		
	Yes / No	Available

Appendix A 2: Comparison of reputation systems [SaSi05, 56]

	Conceptual model	Information source	Visibility	Model's granularity	Agent behavior assumptions	Boolean exchanged information	Trust-Rep reliability measure	Model type
S. Marsh	GT	DI	S	CD	NA[a]	NA[a]	No	Trust
Online Rep models	GT	WI	G	NCD	0	No	No[b]	Rep
Sporas	GT	WI	G	NCD	0	No	Yes	Rep
Histos	GT	DI+WI[c]	S	NCD	0	No	No	Rep
Schillo et al.	GT	DI, DO, WI	S	NCD	1	Yes	No	Trust
A.-Rahman and Hailes	GT	DI, WI[d]	S	CD	2	4 trust values	No	Trust Rep
Esfandiary and Chandrasaekharan	GT	DI, DO, WI, P	S	CD	0	No	No	Trust
Yu and Singh	GT	DI, WI	S	NCD	0	No	No	Trust Rep
Sen and Sajja	GT	DI, DO, WI[e]	S	NCD	2[f]	Yes	No	Rep
AFRAS	GT	DI+WI[c]	S	NCD	2	No	Yes	Rep
Carter et al.	GT	WI[g]	G	NCD	0	No	No	Rep
Castelfranchi and Falcone	C	NA[h]	S	CD	NA[h]	No	NA[h]	Trust
ReGreT	GT	DI+WI+SI+P[c]	S	CD	2	No	Yes	Trust Rep

[a] There is no exchange of information between agents.

[b] Reliability is based on the number of ratings.

[c] The '+' symbol means the model combines the information sources to obtain a final trust/reputation value.

[d] Direct experiences are used to compare the point of view of these witnesses with the direct perception of the agent and then be able to adjust the information coming from them accordingly.

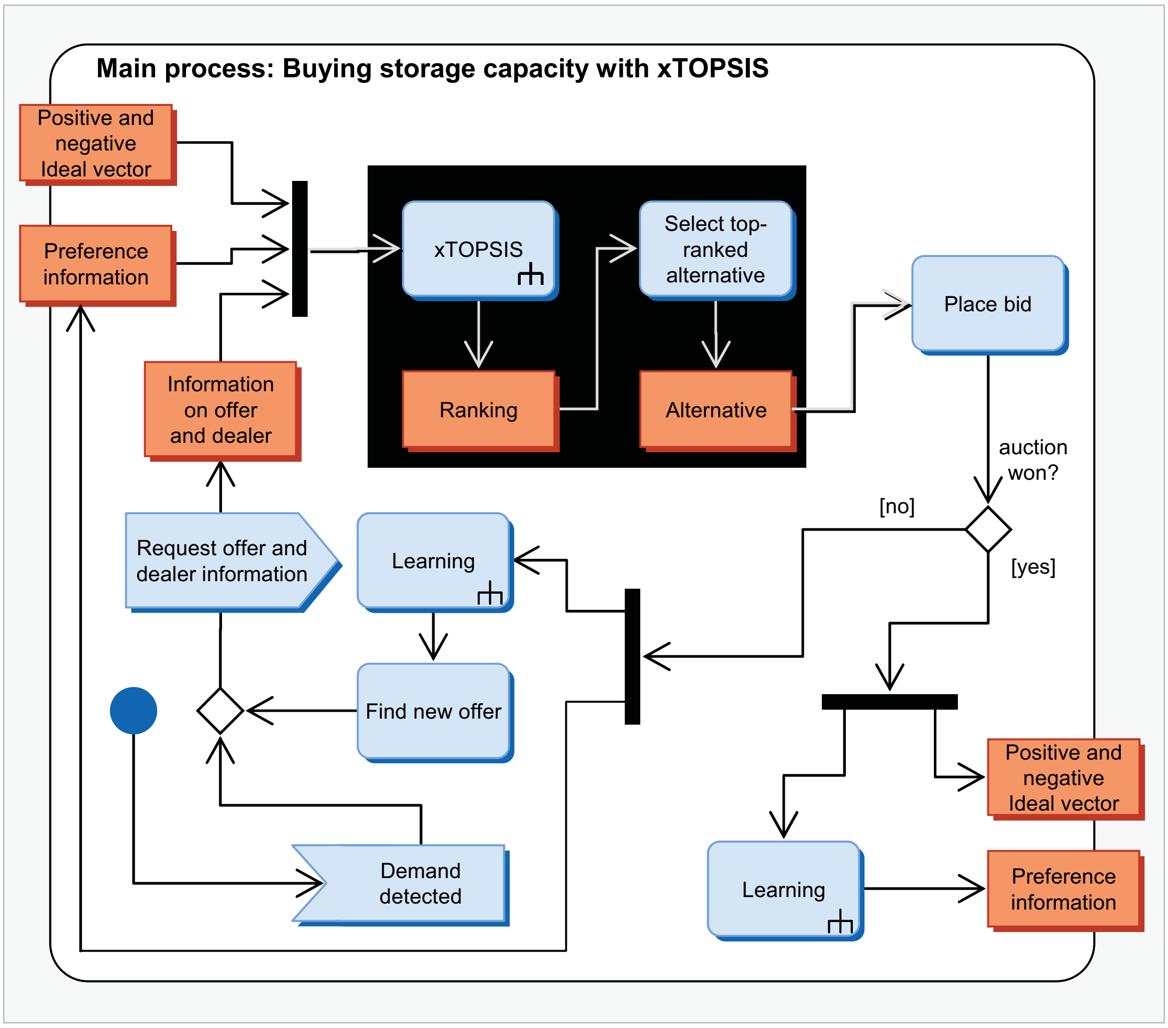
[e] Because the objective of this work was to study how agents use word-of-mouth reputations to select on of several partners, agents only use witness information to take decisions.

[f] Liars are assumed to lie consistently.

[g] Besides information coming from other users (WI) there is a central authority that monitors the agents' behavior and uses that information to build reputation.

[h] In the description of the model it is not specified how the agents obtain the information to build their beliefs.

Appendix A 3: Main process of buying storage capacity with xTOPSIS



Appendix B: Case Study

Situation

Our DM, a new entrant in a sales company, is supposed to pick a brandnew middle class car from a list of seven alternatives. He decides on the basis of five criteria, in which all alternatives differ from each other (Appendix B 1).[1]

Non-discriminating criteria in which all alternatives are equal or very similar, are disregarded[2]; such aspects include the required petrol standard, 95 RON[3] (Eurosuper), the emission level (EURO IV), and the Euro NCAP safety assessment (all cars have been rated with five stars).

With exception of the trunk volume, all data is based on manufacturer information drawn from technical specifications on the respective German website. Since trunk volume appears to differ in the norms of measuring, data from recent tests of the ADAC, the *General German Automobile Association*, is taken into consideration. Despite the difference of their units, all dimensions are scaled on a ratio level.

Appendix B 1: Criteria in the car comparison

Criterion	**Price**	**Fuel consumption**	**Carbon dioxide emission**	**Acceleration**	**Trunk volume**
	Manufacturer's list price in Germany	95 RON Eurosuper, combined (in town, out of town)	Combined (in town, out of town)	Acceleration (from 0 to 100 kmph)	Storage volume of the trunk, without folded seats
Unit measured	EUR	Ltr/100km	g/km	sec	Ltr
	Euros	*Liters per 100 kilometer*	*Grams per kilometer*	*Seconds*	*Liter*
Source	Manufacturer websites				ADAC
Goal	Minimize	Minimize	Minimize	Minimize	Maximize

The set of alternatives includes seven models of different brands which have been chosen in accordance with a similar target market segment; in terms of premium

1 Similar problems with different criteria and alternatives are presented by [BMP+00, 91–93], [YoHw95, 24].

2 Engine power was disregarded because in the set of alternatives it correlated strongly with acceleration (correlation coefficient of 0.7932).

3 Research Octane Number

brands this may be disputed, but since the Ford's basic price exceeds the prices of the Alfa Romeo, the Audi A4, the Saab 9-3 and the Volvo S40, we included the Mondeo.

Appendix B 2: Car selection and information sources

Brand	Model	Source of information	
		All data (except trunk volume)	Trunk volume
Alfa Romeo	159 1.8 MPI 16V	[Fiat08, 3], [Fiat08, 16-17]	[Thyw05c, 4]
Audi	A4 Attraction 1.8TFSI	[Audi08a, 4], [Audi08b]	[Sipp08, 6]
BMW	318i	[BMW08a, 3], [BMW08b, 23-24]	[Thyw05a p. 4]
Ford	Mondeo Ghia 2.0l	[Ford07, 29], [Ford08, 4]	[Ruhd07a, 5]
Mercedes	C180 Kompressor	[Daim07, 2], [Daim08, 5]	[Ruhd07b, 6]
Saab	9-3 1.8i M5	[Saab07, 3], [Saab08]	[Thyw04b, 4]
Volvo	S40 1.6	[Volv08a, 3], [Volvo08b]	[Thyw04a, 4]

All cars are four doors, sedan body style (though in case of the Ford Mondeo, the sedan is more expensive than the station wagon) and basic editions with manual transmission, in order to be competitive as well as comparable in all criteria (Appendix B 2).

Decision matrix

The decision matrix in its initial appearance is presented below (Appendix B 3).

Appendix B 3: Initial decision matrix for car purchase

Brand	Model	Price EUR	Fuel consumption Ltr/100 km	Carbon dioxide emission g/km	Acceleration (0-100 kmph) sec	Trunk volume Ltr
Alfa Romeo	159 1.8 MPI 16V	24,550	7.6	179	10.2	445
Audi	A4 Attraction 1.8TFSI	25,900	7.1	169	10.5	380
BMW	318i	27,300	7.9	142	9.1	405
Ford	Mondeo Ghia 2.0l	26,000	7.9	189	9.9	515
Mercedes	C180 Kompressor	31,089	7.6	177	9.5	350
Saab	9-3 1.8i M5	25,650	7.7	183	11.5	440
Volvo	S40 1.6	21,450	7.2	171	11.9	404

We will later apply MCDM methods which require normalized attributes. For this reason we transform the initial decision matrix linearly and receive a normalized decision matrix (Appendix B 4), e.g. the most expensive car, the Mercedes, has a normalized price value of zero, whereas the second cheapest car, the Alfa Romeo, receives a normalized price value of 0.67839. Where applicable, best values are emphasized in blue, whereas worst values are highlighted in red.

Appendix B 4: Normalized decision matrix

Brand	Model	Price	Fuel consumption	Carbon dioxide emission	Acceleration (0-100 kmph)	Trunk volume
Alfa Romeo	159 1.8 MPI 16V	0.67839	0.37500	0.21277	0.60714	0.57576
Audi	A4 Attraction 1.8TFSI	0.53833	**1.00000**	0.42553	0.50000	0.18182
BMW	318i	0.39309	**0.00000**	**1.00000**	**1.00000**	0.33333
Ford	Mondeo Ghia 2.0l	0.52796	**0.00000**	**0.00000**	0.71429	**1.00000**
Mercedes	C180 Kompressor	**0.00000**	0.37500	0.25532	0.85714	**0.00000**
Saab	9-3 1.8i M5	0.56427	0.25000	0.12766	0.14286	0.54545
Volvo	S40 1.6	**1.00000**	0.87500	0.38298	**0.00000**	0.32727

Dominance Principle

In the next step, we compare the cars pairwise and try to find out whether one car is dominated by another in all attributes and can be withdrawn from further consideration. The dominance test reveals that the Alfa Romeo beats the Saab in all attributes and will be always preferred to it. Therefore we could exclude the Saab from further contemplation.

Maximin and Maximax strategy

If we had no information on the DM's preference structure, we could now merely rely on the Maximin or the Maximax method (Appendix B 5). According to the former, we would decide on the Alfa 159, since the weakest attribute, acceleration, is a flaw the DM could comparably live with.

On the other side, the Maximax method only tells us which cars are *not* to be taken into consideration: the Alfa Romeo and the Mercedes. Their strongest attribute never constitutes a comparative advantage, so both would be eliminated from the set. A decisive result is not presented – our DM is indifferent between the remaining four cars.

Appendix B 5: Deciding without preference – Maximax and Maximin method

Brand	Model	Minimum row value	Maximum row value
Alfa Romeo	159 1.8 MPI 16V	**0.21277**	**0.67839**
Audi	A4 Attraction 1.8TFSI	0.18182	**1.00000**
BMW	318i	**0.00000**	**1.00000**
Ford	Mondeo Ghia 2.0l	**0.00000**	**1.00000**
Mercedes	C180 Kompressor	**0.00000**	**0.85714**
Volvo	S40 1.6	**0.00000**	**1.00000**
Maximin	Maximum of Minimum		
Maximax	Maximum of Maximum		

<u>Satisficing</u>

The application of satisficing does not presume normalized values, but requires aspiration levels for each attribute. We assume our DM provides the thresholds matrix below (Appendix B 6).

Appendix B 6: Aspiration levels for satisficing

Price **EUR**	**Fuel consumption** **Ltr/100 km**	**Carbon dioxide emission** **g/km**	**Acceleration (0-100 kmph)** **Sec**	**Trunk volume** **Ltr**
30,000	7.6	180	10.5	400
Minimize!	Minimize!	Minimize!	Minimize!	Maximize!

On the one hand, the Conjunctive approach results in a distinctive recommendation for the Alfa 159 (Appendix B 7, attributes marked in orange refer to the elimination reason):

Appendix B 7: Satisficing with the Conjunctive approach

Brand	Model	Price EUR	Fuel consumption Ltr/100 km	Carbon dioxide emission g/km	Acceleration (0-100 kmph) sec	Trunk volume Ltr
Alfa Romeo	159 1.8 MPI 16V	24,550	7.6	179	10.2	445
~~Audi~~	~~A4 Attraction 1.8TFSI~~	25,900	7.1	169	10.5	380
~~BMW~~	~~318i~~	27,300	7.9	142	9.1	405
~~Ford~~	~~Mondeo Ghia 2.0l~~	26,000	7.9	189	9.9	515
~~Mercedes~~	~~C180 Kompressor~~	31,089	7.6	177	9.5	350
~~Saab~~	~~9-3 1.8i M5~~	25,650	7.7	183	11.5	440
~~Volvo~~	~~S40 1.6~~	21,450	7.2	171	11.9	404

On the other hand, the Disjunctive approach does not shrink the set of alternatives at all; no car fails to meet all thresholds, thus those have to be tightened in order to cut down the list.

<u>Lexicographic methods</u>

The next two techniques, the Lexicographic method and the Lexicographic Semiorder, ask for a preference order of attributes. We assume the most important issue is the price, followed by fuel consumption, carbon dioxide emission, acceleration and finally trunk volume. While the Lexicographic method immediately selects the cheapest car (the Volvo), we use the Lexicographic Semiorder and define the following difference tolerances within which the DM is indifferent (Appendix B 8).

Appendix B 8: Indifference ranges

Price EUR	Fuel consumption Ltr/100 km	Carbon dioxide emission g/km	Acceleration (0-100 kmph) sec	Trunk volume Ltr
6,000	0.5	15	1.0	50

The indifference range for the price is artificial – the Volvo is *so* extraordinary cheap, a lower indifference threshold would barely change the result from the Lexicographic approach. Again, attributes highlighted in red indicate the knock-out criterion for the respective car, while blue colored attributes represent the *considered* benchmark for each attribute (Appendix B 9). The first car we eliminate is the Mercedes (due to the exorbitant price), followed by the BMW, the Ford and the Saab (because of their high fuel consumption, compared to the Audi). The remaining three cars do not differ *significantly* in terms of carbon dioxide emission, but when it comes to acceleration, the Volvo surrenders. Since the Audi's trunk is much smaller than the Alfa's, the car of choice is once more the Alfa 159.

Appendix B 9: Lexicographic Semiorder

Brand	**Model**	**Price** **EUR**	**Fuel con-sumption** **Ltr/100 km**	**Carbon dioxide emission** **g/km**	**Accelera-tion (0-100 kmph)** **sec**	**Trunk volume** **Ltr**
Alfa Romeo	159 1.8 MPI 16V	24,550	7.6	179	10.2	445
~~**Audi**~~	~~A4 Attraction 1.8TFSI~~	25,900	7.1	169	10.5	380
~~**BMW**~~	~~318i~~	27,300	7.9	142	9.1	405
~~**Ford**~~	~~Mondeo Ghia 2.0l~~	26,000	7.9	189	9.9	515
~~**Mercedes**~~	~~C180 Kompressor~~	31,089	7.6	177	9.5	350
~~**Saab**~~	~~9-3 1.8i M5~~	25,650	7.7	183	11.5	440
~~**Volvo**~~	~~S40 1.6~~	21,450	7.2	171	11.9	404

<u>Elimination by Aspects</u>

Now we turn to the EbA method: again we need standards to be satisfied and we refer to those used for satisficing (Appendix B 6, p. 111). We embark on the fuel consumption attribute being the most discriminating standard and exclude three cars (BMW, Ford, Saab). In the next step we use the trunk volume standard to remove two cars (Audi, Mercedes) from our set. Finally, we realize the Volvo does not match the required acceleration standard; so again, the Alfa 159 prevails (Appendix B 10).

Appendix B 10: Elimination by aspects

Brand	Model	Price EUR	Fuel consump-tion Ltr/100 km	Carbon dioxide emission g/km	Accel-eration (0-100 kmph) sec	Trunk volume Ltr
Alfa Romeo	159 1.8 MPI 16V	24,550	7.6	179	10.2	445
~~Audi~~	~~A4 Attraction 1.8TFSI~~	25,900	7.1	169	10.5	380
~~BMW~~	~~318i~~	27,300	7.9	142	9.1	405
~~Ford~~	~~Mondeo Ghia 2.0l~~	26,000	7.9	189	9.9	515
~~Mercedes~~	~~C180 Kompressor~~	31,089	7.6	177	9.5	350
~~Saab~~	~~9-3 1.8i M5~~	25,650	7.7	183	11.5	440
~~Volvo~~	~~S40 1.6~~	21,450	7.2	171	11.9	404

Simple Additive Weighting and Weighted Product Method

The next techniques all ask for the explicit formulation of relative importance information on attributes in values, i.e. measuring weights. The process of weight estimation is not subject here; indeed, it contributes to the basic challenges a DM is confronted with, but we assume instead that the stakeholders (i.e. the boss, the family or other relatives) have worked out the following weight vector (Appendix B 11):

Appendix B 11: Weights vector

Price	Fuel consumption	Carbon dioxide emission	Acceleration (0-100 kmph)	Trunk volume
30 %	20 %	9 %	24 %	17 %

With help of these weights, we calculate the SAW score first and compare it directly to the WPM result afterwards. For the SAW method, we embark on the normalized decision matrix used before (Appendix B 4, p. 110) and calculate a new matrix with weighted attribute values.

The last column includes the respective score value and again, the best (worst) alternative is highlighted in blue (red) (Appendix B 12).

Appendix B 12: Simple Additive Weighting method

Brand	Model	Price	Fuel consumption	Carbon dioxide emission	Acceleration (0-100 kmph)	Trunk volume	Score V_i
Alfa Romeo	159 1.8 MPI 16V	0.20352	0.075	0.00019	0.14571	0.09788	0.5223
Audi	A4 Attraction 1.8TFSI	0.1615	0.2	0.00038	0.12	0.03091	0.51279
BMW	318i	0.11793	0	0.0009	0.24	0.05667	0.4155
Ford	Ghia 2.0l	0.15839	0	0	0.17143	0.17	0.49982
Mercedes	C180 Kompressor	0	0.075	0.00023	0.20571	0	**0.28094**
Saab	9-3 1.8i M5	0.16928	0.05	0.00011	0.03429	0.09273	0.34641
Volvo	S40 1.6	0.3	0.175	0.00034	0	0.05564	**0.53098**

Using the same weights, the WPM leads to different results (Appendix B 13). Since this method includes three steps, we will illustrate the calculation with one example here, the Alfa 159. The score was calculated with the formula (Subsection 3.3.5.2)

$$\frac{V_i}{V\left(A^*\right)} = \frac{\prod_{j=1}^{n}\left(v_{ij}\right)^{w_j}}{\prod_{j=1}^{n}\left(v_j^*\right)^{w_j}}.$$

First step:

$$V_{Alfa} = \left(24{,}550 \text{ EUR}\right)^{-0,3} \cdot \left(7.6 \ \frac{\text{Ltr}}{100 \text{ km}}\right)^{-0,2} \cdot \left(179 \ \frac{\text{g}}{\text{km}}\right)^{-0,09} \cdot \left(10.2 \text{ sec}\right)^{-0,24} \cdot \left(445 \text{ Ltr}\right)^{0,17}$$

$$V_{Alfa} \approx 0.05164$$

Second step:

As we need a reference point for the WPM scale, we assess the ideal solution *V(A*)* by combining the best values for each attribute:

$$V\left(A^{*}\right)=\prod_{j=1}^{n}\left(v_{j}^{*}\right)^{w_{j}} \text{ with } v_{j}^{*}=\max v_{ij}$$

$$V\left(A^{*}\right)=\left(21{,}450 \text{ EUR}\right)^{-0,3}\cdot\left(7.1\ \frac{\text{Ltr}}{100 \text{ km}}\right)^{-0,2}\cdot\left(142\ \frac{\text{g}}{\text{km}}\right)^{-0,09}\cdot\left(9.1 \text{ sec}\right)^{-0,24}\cdot\left(515 \text{ Ltr}\right)^{0,17}$$

$$V\left(A^{*}\right)\approx 0.05744$$

Third step:

Now we get the score for the Alfa taking the ratio of V_{Alfa} *and* $V(A^{*})$,

$$\frac{V_{Alfa}}{V\left(A^{*}\right)}=\frac{0.05164}{0.05744}\approx 0.899\,.$$

Appendix B 13: Weighted Product Method

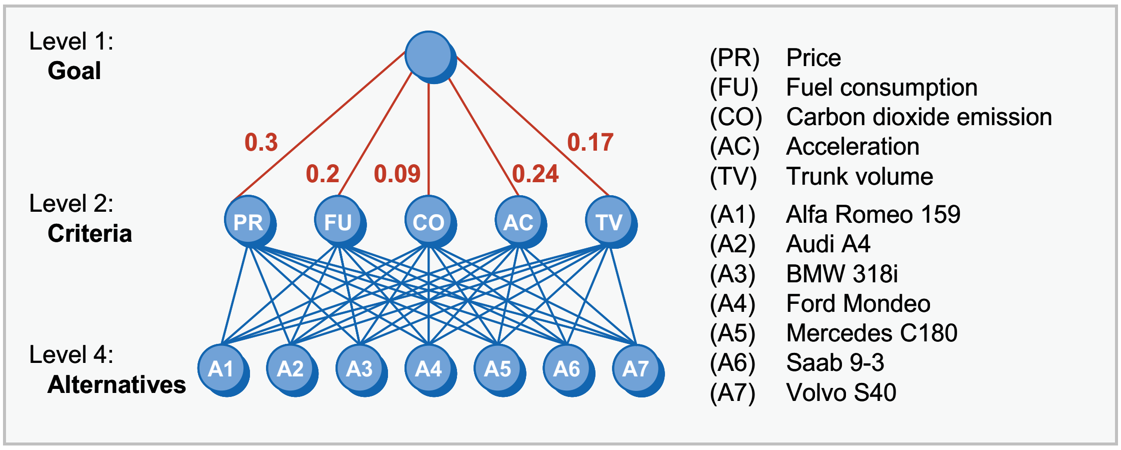
Brand	**Model**	**Price** EUR	**Fuel consumption** Ltr/100 km	**Carbon dioxide emission** g/km	**Acceleration (0-100 kmph)** sec	**Trunk volume** Ltr	**Score** $\frac{V_i}{V\left(A^{*}\right)}$
Alfa Romeo	159 1.8 MPI 16V	0.04819	0.66656	0.99534	0.57271	2.81982	0.899
Audi	A4 Attraction 1.8TFSI	0.04743	0.67569	0.99539	0.56874	2.74513	0.867
BMW	318i	0.04668	0.66142	0.99555	0.58861	2.77503	0.8741
Ford	Ghia 2.0l	0.04737	0.66142	0.99529	0.57683	2.89073	**0.9053**
Mercedes	C180 Kompressor	0.0449	0.66656	0.99535	0.58257	2.70702	**0.8178**
Saab	9-3 1.8i M5	0.04756	0.66482	0.99532	0.55646	2.81441	0.8581
Volvo	S40 1.6	0.05018	0.6738	0.99538	0.55191	2.77386	0.8971

Although both methods use the same weights, they produce different results when it comes to the final recommendation: the SAW prefers the Volvo, the WPM suggests the Ford. This stems from the normalization methods – being the weakest choice in fuel consumption and carbon dioxide emission, the Ford's outcome on these dimensions is set to zero in the SAW method; one strength (trunk) cannot compensate for these two flaws. The Volvo in contrast has to cope with only one relatively weak attribute (acceleration).

Analytic Hierarchy Process

Now we examine the course of action for the Analytic Hierarchy Process. First, we depict the decision situation in a hierarchy with three levels. The superior goal weights vector consists of the elicited relative contributions of each criterion for the overall goal. We take our weights vector (Appendix B 11, p. 114) and assume it is based on pairwise comparisons; then we attach the weight values to their respective edge, highlighted in red color (Appendix B 14).

Appendix B 14: Hierarchy for the AHP method



Secondly, we calculate the five weight vectors for the five criteria (which correspond with blue edges between the level 2 and level 3 nodes). A vector is determined by comparing pairwise the alternatives with regard to the respective criterion, e.g. how many times is the price of the Alfa better than the price of the Audi, and by calculating the geometric mean for each alternative afterwards[4]. This means we have three steps for each criterion:

1. Constructing a pairwise comparison matrix,
2. calculating geometric means for each alternative, and
3. applying a linear transformation to normalize the means into a weights vector (Appendix B 15, where these weights are highlighted in red).

4 Although Saaty recommends the use of his eigenvector method, we use the simpler geometric mean calculation here and omit the consistency check.

The other four vectors are given for further calculation and are not explicitly derived here (Appendix B 16).

Appendix B 15: The pairwise comparison matrix and the weight vector for the price criterion

PR	A1	A2	A3	A4	A5	A6	A7		Geom. Mean	Normalized weight
A1	1	1	3	1	7	1	1/3	**A1**	1.32047	0.13856
A2	1	1	1	1	5	1	1/5	**A2**	1	0.10493
A3	1/3	1	1	1	3	1	1/7	**A3**	0.75731	0.07947
A4	1	1	1	1	5	1	1/5	**A4**	1	0.10493
A5	1/7	1/5	1/3	1/5	1	1/5	1/9	**A5**	0.23726	0.02490
A6	1	1	1	1	5	1	1/5	**A6**	1	0.10493
A7	3	5	7	5	9	5	1	**A7**	4.21471	0.44227
								Σ	9.52975	

Step 1 → Step 2 → Step 3

Finally, the resulting five (7x1)-vectors display the relative contribution of each car with regard to the specific criterion; we can merge these five columns into a (7x5) matrix. This comes in handy for determining the composite values, because we can easily multiply this matrix with the goal vector for the five criteria (Appendix B 16).

Appendix B 16: Weight vectors for all five criteria

	Normalized weights						Goal weights		Score V_i
Brand	**PR**	**FU**	**CO**	**AC**	**TV**				
Alfa Romeo	0.1385	0.07269	0.07424	0.12399	0.16212				0.12011
Audi	0.1049	0.38069	0.13417	0.08729	0.0467		0.3		0.14858
BMW	0.0794	0.02942	0.51336	0.31794	0.06092		0.2		0.16259
Ford	0.1049	0.02942	0.03554	0.16971	0.48692	×	0.09	=	0.16407
Mercedes	0.0249	0.07269	0.08685	0.24372	0.03172		0.24		0.09371
Saab	0.1049	0.06928	0.05424	0.03161	0.15071		0.17		**0.0834**
Volvo	0.4422	0.3458	0.10161	0.02575	0.06092				**0.2275**
Σ (column)	1	1	1	1	1		1		1

We receive the five score values by conducting the matrix multiplication as mentioned. Say, for the Alfa Romeo one can compute the score value V_{Alfa} by adding the Alfa's criteria contributions weighted with goal weights already given as follows:

$$V_1 = \underbrace{(0.13856 \cdot 0.3)}_{\text{PR contribution}} + \underbrace{(0.07269 \cdot 0.2)}_{\text{FU contribution}} + \underbrace{(0.07424 \cdot 0.09)}_{\text{CO contribution}} + \underbrace{(0.12399 \cdot 0.24)}_{\text{AC contribution}} + \underbrace{(0.16212 \cdot 0.17)}_{\text{TV contribution}}$$

$$V_1 \approx 0.12$$

Thus, with a score value of $V(A_7) = 0.228$ the Volvo emerges as the best choice. This is the same result as in the SAW method, due to the similarity of both methods in summarizing the partial values: The relative contributions of the AHP can be compared to the absolute values of the SAW method.

Technique for Order Preference by Similarity to Ideal Solution

We start with normalizing the decision matrix, but this time, we make use of the vector transformation which will lead to results different from the linear one (Appendix B 17).

Appendix B 17: Vector normalized decision matrix

Brand	Model	Price	Fuel consumption	Carbon dioxide emission	Acceleration (0-100 kmph)	Trunk volume
Alfa Romeo	159 1.8 MPI 16V	0.39380	0.37569	0.36077	0.37971	0.39786
Audi	A4 1.8TFSI	0.37328	**0.40214**	0.38212	0.36886	0.33975
BMW	318i	0.35413	**0.36142**	**0.45478**	**0.42561**	0.36210
Ford	Ghia 2.0l	0.37184	**0.36142**	**0.34168**	0.39122	**0.46045**
Mercedes	C180 Komp.	**0.31097**	0.37569	0.36485	0.40769	**0.31293**
Saab	9-3 1.8i M5	0.37691	0.37081	0.35289	0.33679	0.39339
Volvo	S40 1.6	**0.45071**	0.39656	0.37765	**0.32547**	0.36121

Continuing with weighting the results, we hold on to the same trade-off values as used before in SAW, WPM and AHP (Appendix B 11, p. 114). Thus, we receive a matrix with weighted normalized values (Appendix B 18).

Appendix B 18: Weighted normalized decision matrix

Brand	Model	Price	Fuel con-sumption	Carbon dioxide emission	Accelera-tion (0-100 kmph)	Trunk volume
Alfa Romeo	159 1.8 MPI 16V	0.11814	0.07514	0.03247	0.09113	0.06764
Audi	A4 1.8TFSI	0.11198	**0.08043**	0.03439	0.08853	0.05776
BMW	318i	0.10624	**0.07228**	**0.04093**	**0.10215**	0.06156
Ford	Ghia 2.0l	0.11155	**0.07228**	**0.03075**	0.09389	**0.07828**
Mercedes	C180 Komp.	**0.09329**	0.07514	0.03284	0.09785	**0.05320**
Saab	9-3 1.8i M5	0.11307	0.07416	0.03176	0.08083	0.06688
Volvo	S40 1.6	**0.13521**	0.07931	0.03399	**0.07811**	0.06140

Again, best (and worst) values are highlighted in blue (red) – those values comprise the positive (negative) ideal solution in the next step. Thus, we receive the following two vectors (Appendix B 19). These two vectors span a convex set of alternatives among which our seven cars are located.

Appendix B 19: Positive and negative ideal solution

Reference point	Price	Fuel con-sumption	Carbon dioxide emission	Accelera-tion (0-100 kmph)	Trunk volume
Positive ideal solution	**0.13521**	**0.08043**	**0.04093**	**0.10215**	**0.07828**
Negative ideal solution	**0.09329**	**0.07228**	**0.03075**	**0.07811**	**0.05320**

To determine the final ranking, we calculate *separation* measures S^+_i (S^-_i) for each alternative to these reference points. We retrieve the closeness of the Alfa Romeo to the positive ideal solution from

$$
\begin{aligned}
S^+_{Alfa} &= \sqrt{\sum_{j=1}^{n=5}\left(w_j v_{Alfa\,j} - w_j v_j^+\right)^2} = \sqrt{(0.11814-0.13521)^2+\ldots+(0.06764-0.07828)^2} \\
&= \sqrt{(-0.01707)^2+(-0.00529)^2+(-0.00846)^2+(-0.01102)^2+(-0.01064)^2} \\
&\approx 0.02501 \\
S^-_{Alfa} &\approx 0.03172
\end{aligned}
$$

and compute the *similarity measure* R_{Alfa} with

$$R_{Alfa} = \frac{S^-_{Alfa}}{S^+_{Alfa} + S^-_{Alfa}} = \frac{0.03172}{0.02501 + 0.03172} \approx 0.55916 .$$

Sorting the alternatives according to the similarity measure, we get a ranking with a clear recommendation for the Volvo – and the good advice not to consider the Mercedes any further (Appendix B 20). Regarding the closeness indices, we see that the Alfa is *in absolute terms* closer to the positive ideal solution, but – due to some criteria values – also closer to the negative ideal one. The Volvo beats the Alfa because of compensating for the lack of excellence in acceleration with possessing relatively strong figures in terms of price and fuel consumption. This indicates the similarity between the SAW and TOPSIS (i.e. the additive compensation between criteria).

Appendix B 20: Similarity to positive ideal solution

Brand	Model	Closeness to...		Similarity	Rank
		positive ideal solution	negative ideal solution		
Alfa Romeo	159 1.8 MPI 16V	**0.02501**	0.03173	0.55916	2
Audi	A4 1.8TFSI	0.03448	0.02363	0.40659	6
BMW	318i	0.03443	0.03031	0.4682	4
Ford	Ghia 2.0l	0.02825	0.03481	0.55199	3
Mercedes	C180 Komp.	**0.04998**	**0.02005**	**0.28626**	7
Saab	9-3 1.8i M5	0.03461	0.0243	0.41246	5
Volvo	S40 1.6	0.03019	**0.04341**	**0.58979**	**1**

Finally, we need to come back to the normalization mechanism: The choice of the technique exerts influence on the final ranking order; if we had applied the *linear* normalization, the Audi for instance would have come out much better and the winner would have been the Alfa (Appendix B 21). Thus, a sensitivity analysis is compulsory to make an entirely satisfactory decision.

Appendix B 21: Similarity and Ranking for linear normalization

Brand	Model	Similarity	Rank
Alfa Romeo	159 1.8 MPI 16V	**0.57131**	**1**
Audi	A4 1.8TFSI Attraction	0.54977	3
BMW	318i	0.49529	5
Ford	Ghia 2.0l	0.51685	4
Mercedes	C180 Kompressor	**0.37028**	7
Saab	9-3 1.8i M5	0.39788	6
Volvo	S40 1.6	0.56443	2

ELECTRE

Last, we use an outranking technique to see if we can elicit a distinct recommendation for our case. Because it is common practice to use a decision matrix with vector normalized values and since we assume the same weights as before (Appendix B 11, p. 114), we start with the weighted normalized decision matrix as in the TOPSIS description (Appendix B 18, p. 120). On the grounds of this information we use the outranking relation S and elicit the concordance indices to assess the strength of support for the statement that one car outranks another. With

$$con_{kl} = con(A_k S A_l) = \sum_{\{j : a_{kj} \geq a_{lj}\}} w_j \text{ with } k,l \in \{1,\ldots,7\} \wedge k \neq l \text{ ,}$$

we receive for the outranking relation $A_{Alfa} S A_{Audi}$ that the Alfa 159 excels the Audi A4 in price, acceleration and trunk volume. The concordance index of the statement that the Alfa is better than the Audi is equal to the sum of the corresponding weights, thus 0.71 (w_{price}= 30 %, $w_{acceleration}$= 24 %, w_{trunk_volume}= 17 %). After 7 × 6 = 42 comparisons (outranking relations are not reflexive), we obtain the complete matrix with concordance indices (Appendix B 22).

Appendix B 22: Concordance indices

	Alfa Romeo	Audi	BMW	Ford	Mercedes	Saab	Volvo
Alfa Romeo		0.71	0.67	0.59	0.67	1	0.41
Audi	0.29		0.5	0.59	0.83	0.53	0.53
BMW	0.33	0.5		0.53	0.8	0.33	0.5
Ford	0.41	0.41	0.67		0.47	0.41	0.41
Mercedes	0.53	0.24	0.2	0.53		0.53	0.24
Saab	0	0.47	0.67	0.59	0.47		0.41
Volvo	0.59	0.47	0.5	0.59	0.76	0.59	

Afterwards we turn to the discordance indices, the strength of dissent on the statement that one car outranks another. With

$$dis_{kl} = dis(A_k SA_l) = \frac{\max\limits_{\{j:a_{kj}<a_{lj}\}} \left| w_j \cdot a_{kj} - w_j \cdot a_{lj} \right|}{\max\limits_{j} \left| w_j \cdot a_{kj} - w_j \cdot a_{lj} \right|} \text{ with } k,l \in \{1,\ldots,m\} \wedge k \neq l.$$

we compute the strength of discordance for statement that the Alfa outranks the Audi in two steps.

First, with regard to the nominator of the fraction, we estimate the maximum difference on weighted normalized values between the two cars from the subset of criteria in which the Alfa is not outdoing the Audi, fuel consumption and carbon dioxide emission:

$$\begin{aligned}\max_{\{j:a_{Alfa\,j}<a_{Audi\,j}\}} \left| w_j \cdot a_{Alfa\,j} - w_j \cdot a_{Audi\,j} \right| &= \max\left(|0.07514 - 0.08043|;\ |0.03247 - 0.03439| \right) \\ &= \max(0.00529;\ 0.00192) = 0.00529\end{aligned}$$

In the second step, the denominator, which is equivalent to a scale coefficient, is computed from the maximum difference on weighted normalized values between the two cars on all criteria:

$$\max_j \left| w_j \cdot a_{Alfa\,j} - w_j \cdot a_{Audi\,j} \right|$$
$$= \left(\left|0.11814 - 0.11198\right|;\ \left|0.07514 - 0.08043\right|;\ \left|0.03247 - 0.03439\right|; \right.$$
$$\left. \left|0.09113 - 0.08853\right|;\ \left|0.06764 - 0.05776\right| \right)$$
$$= (0.00616;\ 0.00529;\ 0.00192;\ 0.0026;\ 0.00988)$$
$$= 0.00988$$

Repeating these two steps for all 42 matrix entries, we determine the matrix with discordance indices (Appendix B 23).

Appendix B 23: Discordance indices

	Alfa Romeo	Audi	BMW	Ford	Mercedes	Saab	Volvo
Alfa Romeo		0.53559	0.92565	1	0.27023	0	1
Audi	1		1	1	0.49857	1	1
BMW	1	0.59801		1	0.22037	0.32059	1
Ford	0.61926	0.39693	0.60878		0.15764	0.14372	1
Mercedes	1	1	1	1		1	1
Saab	1	0.84412	1	1	0.8602		1
Volvo	0.76249	0.4483	0.8295	0.71299	0.47071	0.24714	

To qualify the concordance and discordance values, we will now continue with building the *concordance dominance matrix* $\mathbf{F} \in \mathbb{R}^{m \times m}$ and the *discordance dominance matrix* $\mathbf{G} \in \mathbb{R}^{m \times m}$. Therefore we compute the arithmetic mean of each matrix as a threshold value – if a matrix entry is below the threshold, we assume the statement is too weak to be taken seriously. With the mean values $\overline{con} = 0.51119$ ($\overline{dis} = 0.7493$) for the concordance (discordance) indices we receive the concordance dominance matrix (Appendix B 24) and the discordance dominance matrix (Appendix B 25).

Appendix B 24: Concordance dominance matrix

	Alfa Romeo	Audi	BMW	Ford	Mercedes	Saab	Volvo
Alfa Romeo		1	1	1	1	1	0
Audi	0		0	1	1	1	1
BMW	0	0		1	1	0	0
Ford	0	0	1		0	0	0
Mercedes	1	0	0	1		1	0
Saab	0	0	1	1	0		0
Volvo	1	0	0	1	1	1	

Appendix B 25: Discordance dominance matrix

	Alfa Romeo	Audi	BMW	Ford	Mercedes	Saab	Volvo
Alfa Romeo		1	0	0	1	1	0
Audi	0		0	0	1	0	0
BMW	0	1		0	1	1	0
Ford	1	1	1		1	1	0
Mercedes	0	0	0	0		0	0
Saab	0	0	0	0	0		0
Volvo	0	1	0	1	1	1	

Finally, we aggregate the two matrices into a dominance matrix, which can be understood as a table with measures indicating that the outranking statement between two cars is supported *and* not rejected or vice versa (Appendix B 26). We read this table row-wise and eliminate all cars in columns where the pivotal entry is a one, namely the Audi, the BMW, the Ford, the Mercedes and the Saab. Regarding the remaining two models, we cannot distinguish between them: the Alfa Romeo and the Volvo are "incomparable" and thus of equal value to the DM.

Appendix B 26: Dominance matrix

	Alfa Romeo	~~Audi~~	~~BMW~~	~~Ford~~	~~Mercedes~~	~~Saab~~	Volvo
Alfa Romeo		1	0	0	1	1	0
Audi	0		0	0	1	0	0
BMW	0	0		0	1	0	0
Ford	0	0	1		0	0	0
Mercedes	0	0	0	0		0	0
Saab	0	0	0	0	0		0
Volvo	0	0	0	1	1	1	

<u>Conclusion</u>

The application of different normalization techniques and MCDM methods has lead to an ambiguous result (Appendix B 27). No specific car dominates in all approaches, but when comparing the rankings we can see two clear tendencies: one against the Mercedes, one in favor of the Volvo.

Appendix B 27: Overview rankings of applied methods

Method / Order	SAW	WPM	AHP	TOPSIS	ELECTRE
1.	**Volvo**	**Ford**	**Volvo**	**Volvo**	**Alfa/ Volvo**
2.	Alfa	Alfa	Ford	Alfa	-
3.	Audi	Volvo	BMW	Ford	-
4.	Ford	BMW	Audi	BMW	-
5.	BMW	Audi	Alfa	Saab	-
6.	Saab	Saab	Mercedes	Audi	-
7.	**Mercedes**	**Mercedes**	**Saab**	**Mercedes**	-

For a more sophisticated comparison with a precise advice, car configurations, interior and exterior furnishings should be equalized in order to eliminate as many objective differences among the cars as possible. The purpose of this case is rather to be illustrative, not to provide a true purchase recommendation.

This work is concerned with the conduct of MCDM by intelligent agents trading commodities in ALNs. These agents consider trustworthiness in their course of negotiation and select offers with respect to product price and seller reputation. To automate the selection process, we seek an appropriate MCDM method that provides clear advice for an agent prior to negotiating. We compare eleven well-known MCDM methods and choose the TOPSIS approach of Hwang and Yoon since it produces comprehensible and plausible results with a justifiable amount of effort. We modify the method and present a draft named xTOPSIS that promises intertemporal performance analysis for further automatation. The resulting tool is finally tested and evaluated in the context of a scenario similar to the Social Knowledge for e-Governance project.

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