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Calculating and Aggregating Direct Trust and Reputation in Organic Computing Systems

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Abstract

The growing complexity of current computer systems requires a high amount of administration, which poses an increasingly challenging task for manual administration. The Autonomic and Organic Computing Initiatives have introduced so called self-x properties, including self-configuration, self-optimization, self-healing, and self-protection, to allow administration to become autonomous. Although research in this area revealed promising results, it expects all participants to further the system goal, i.e, their benevolence is assumed. In open systems, where arbitrary participants can join the systems, this benevolence assumption must be dropped, since such a participant may act maliciously and try to exploit the system. This introduces a not yet considered uncertainty, which needs to be addressed.

In human society, trust relations are used to lower the uncertainty of transactions with unknown interaction partners. Trust is based on past experiences with someone, as well as recommendations of trusted third parties. In this work trust metrics for direct trust, reputation, confidence, and an aggregation of them are presented. While the presented metrics were primarily designed to improve the self-x properties of OC systems they can also be used by applications in Multi-Agent-Systems to evaluate the behavior of other agents. Direct trust is calculated by the Delayed-Ack metric, that assesses the reliability of nodes in Organic Computing systems. The other metrics are general enough to be used with all kinds of contexts and facets to cover any kind of trust requirements of a system, as long as corresponding direct trust values exist. These metrics include reputation (Neighbor-Trust), confidence, and an aggregation of them.

Evaluations based on an Automated Design Space Exploration are conducted to find the best configurations for each metric, especially to identify the importance of direct trust, reputation, and confidence for the total trust value. They illustrate, that reputation, i.e., the recommendations of others, is an important aspect to evaluate the trustworthiness of an interaction partner. In addition, it is shown that a gradual change of priority from reputation to direct trust is preferable instead of a sudden switch when enough confidence in the correctness of ones own experiences is accumulated. All evaluations focus on systems with volatile behavior, i.e., system participants change their behavior over time. In such a system, the ability to adapt fast to behavior changes has turned out to be the most important parameter.

Kurzfassung

Die steigende Komplexität aktueller Systeme benötigt einen hohen Grad an Administration, was eine wachsende Herausforderung für die manuelle Administration darstellt. Die Autonomic- und Organic-Computing Initiativen haben so genannte Selbst-x Eigenschaften vorgestellt, unter anderem Selbst-Konfiguration, Selbst-Optimierung, Selbst-Heilung sowie Selbst-Schutz, die eine autonome Administration erlauben. Obwohl die Forschung in diesem Gebiet erfolgversprechende Ergebnisse geliefert hat, wird von allen Teilnehmern erwartet, dass sie das Systemziel vorantreiben, d.h., ihr Wohlwollen wird vorausgesetzt. In offenen Systemen, in denen beliebige Teilnehmer dem System beitreten können, muss diese Wohlverhaltensannahme fallen gelassen werden, da solche Teilnehmer bösartig handeln und versuchen können, das System auszunutzen.

In einer menschlichen Gesellschaft werden Vertrauensbeziehungen dazu benutzt, die Unsicherheit von Transaktionen mit unbekannten Interaktionspartnern zu mindern. Vertrauen basiert auf den bisherigen Erfahrungen mit Jemandem und auf Empfehlungen von Dritten. In dieser Arbeit werden Trust-Metriken für direkten Trust, Reputation, Konfidenz und deren Aggregation vorgestellt. Obwohl die vorgestellten Metriken hauptsächlich dafür entworfen wurden, die Selbst-x Eigenschaften von Organic-Computing Systemen zu verbessern, können sie ebenso von Applikationen in Multi-Agenten-Systemen benutzt werden, um das Verhalten anderer Agenten einschätzen zu können. Direkter Trust wird durch die Delayed-Ack Metrik berechnet, welche die Zuverlässigkeit von Knoten in Organic-Computing Systemen einschätzt. Die anderen Metriken sind allgemein genug gehalten, um in jedem Kontext und jeder Facette benutzt werden zu können, in dem ein System operiert, solange ein Trust-Wert für direkten Trust existiert. Diese Metriken beinhalten Reputation (Neighbor-Trust), Konfidenz und die Aggregation dieser.

Es werden Evaluationen basierend auf einer automatischen Design Space Exploration durchgeführt, um die beste Konfiguration für jede Metrik zu finden, um dabei speziell die Wichtigkeit von direktem Trust, Reputation und Konfidenz auf den gesamten Trust-Wert zu identifizieren. Sie veranschaulichen, dass Reputation, d.h. die Vorschläge Dritter, ein wichtiger Aspekt ist, um die Vertrauenswürdigkeit eines Interaktionspartners einschätzen zu können. Zusätzlich zeigen sie, dass ein gradueller Wechsel von Reputation zu eigenen Erfahrungen einem plötzlichen Wechsel vorzuziehen ist, wenn genug Zuversicht auf die Korrektheit der eigenen Erfahrungen vorhanden ist. Alle Auswertungen befassen sich mit Systemen mit unbeständigem Verhalten, d.h. Systemteilnehmer ändern ihr Verhalten über die Zeit. In solch einem System hat sich herausgestellt, dass

die Fähigkeit, sich schnell an Verhaltensänderungen anpassen zu können, der wichtigste Faktor ist.

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Contents

List of Abbreviations

ADSE	Automated Design Space Exploration
AVPP	Autonomous Virtual Power Plant
CPU	Central Processing Unit
DFG	Deutsche Forschungsgemeinschaft (German Research Foundation)
DT	Direct Trust
DTC	Direct Trust and Confidence
DTCR	Direct Trust, Confidence and Reputation
EU	European Union
FADSE	Framework for Automated Design Space Exploration
ID	Identifier
JVM	Java Virtual Machine
MAS	Multi-Agent System
NSGAII	Nondominated Sorting Genetic Algorithm II
P2P	Peer-to-Peer
RAND	Random
SMPSO	Speed-constrained Multi-objective Particle Swarm Optimization
TC	Trusted Community
TCP	Transmission Control Protocol
TEM	Trust-Enabling Middleware
TEMAS	Trust-Enabled Multi-Agent System
TMI	Trust Metric Infrastructure
UDP	User Datagram Protocol
UUID	Universally Unique Identifier

1. Introduction

Modern systems consist of a growing number of interacting parts, whose interactions increase in complexity as well. This leads to challenges for their design and administration. A lot of work has to be done at design time to enable the systems to handle all possible situations they need to operate in. Organic Computing (OC) [44] identified the growing complexity as a critical problem and introduced mechanisms for a possible solution. The primary goal of OC is to move decisions from design time to runtime. By giving the system control over its own configuration, an OC system is able to autonomously adapt to at design time unforeseen situations. To achieve this, OC introduced so called self-x properties, i.e., self-configuration, self-optimization, self-healing and self-protection. To implement these properties the systems constantly observe themselves and initiate autonomous reconfigurations when necessary (Observer/Controller paradigm). By enabling autonomous reconfigurations, OC systems are able to react to disturbances without the immediate intervention of a user.

So far, OC systems assume the benevolence of every involved interaction partner to obtain a more robust system using these self-x properties. In open heterogeneous systems, like in cloud [43] or grid [17] computing, this benevolence assumption can no longer hold. In such systems, participants can enter and leave the systems at will. In addition, not every participant is interested in an altruistic cooperation to further the system goal. Some participants might try to exploit the systems or even try to attack and disrupt it. This introduces a new level of uncertainty and risk to the systems, when the participants might have malicious interaction partners.

Human societies cope with uncertain interaction partners, and the possible risks when working with them, by using trust. Trust is a subjective concept, that considers past actions of another person to gauge its upcoming behavior. Trust has shown to be an enabling ability for human societies. With it, one can assess the possible risk that might occur with that interaction. By transferring the concept of trust into OC systems, the described uncertainties and risks can be assessed as well by monitoring and and evaluating the behavior of the system participants. Using this information the self-x properties of OC systems are able to consider the behavior of its participants, even in case of behavior changes, and are therefore able to maintain a more robust configuration in the face of unreliable components. This enables a reliable system out of unreliable components.

In this work I present trust metrics for direct trust, reputation, confidence and an aggregation of them. While the presented metrics were primarily designed to improve the self-x properties of OC systems they can also be used by applications in Multi-Agent-Systems (MAS) [60][61] to assess the behavior of other agents. On the one hand, the metrics focus to improve the self-x properties on middleware level, i.e., without knowledge about the applications running on the middleware, but on the other hand they are designed to be as general as possible where possible. The presented metric for direct trust (Delayed-Ack) focuses on the reliability of nodes in a Multi-Agent-System (MAS) to provide information for suitable targets when assigning or relocating services or agents. The reputation, confidence and aggregation metrics are designed to work with every kind of direct trust value and can therefore be used to process direct trust values of agents as well as nodes.

Chapter 2 describes the OC systems considered in this work, explains the self-x properties in more detail and gives an overview over existing OC systems. After that, the concept of trust is described and defined, giving a more in depth description of the facets considered in this work, followed by a description of the context sensitive and subjective nature of trust. Current trust metrics and frameworks are discussed at the end of the chapter.

Chapter 3 presents the trust metrics for direct trust, reputation, confidence and aggregation with some small evaluations for each metric showing its effectiveness. The Delayed-Ack metric calculates the reliability of nodes, providing direct trust values. The reputation is calculated by the Neighbor-Trust algorithm, which is able to identify lying nodes and only considers trustworthy recommendations. Confidence as a means to assess the accuracy of ones own direct trust value serves as basis to weight direct trust and reputation to a total trust value. Figure 1.1 depicts the relation of the different trust aspects, i.e., direct trust, reputation, and confidence to get a total trust value.

Chapter 4 presents an evaluation based on Automated Design Space Exploration (ADSE). The trust metrics introduced in Chapter 3 are evaluated in a MAS with changing agent behavior. There are two main research questions investigated in this chapter:

1. To identify the effect and importance of the different aspects of trust, including direct trust, reputation, and confidence on a total trust value, i.e., in what situation only some of them are used to make the decision, with which possible partner to interact with.
2. Finding the turning point between reputation (the opinion of others) and direct trust (ones own opinion), when direct trust dominates reputation. The main research question is, if that point can be denominated or if a more fuzzy approach is required.

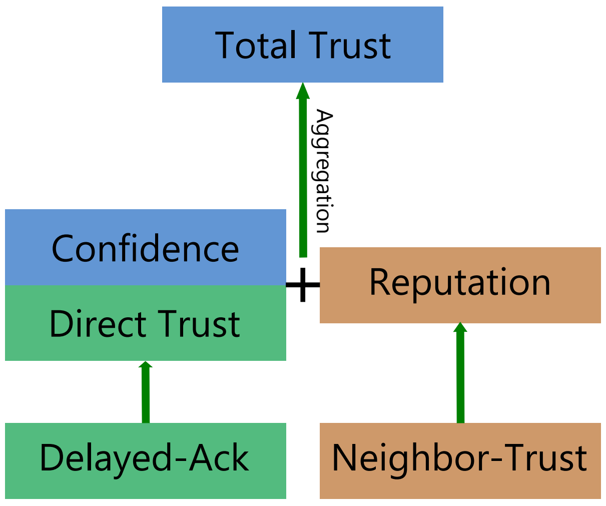


Figure 1.1.: Aggregating direct trust with confidence and reputation to a total trust value including the corresponding metrics described in this work.

These points are investigated in a pure computational system with no human involvement.

Chapter 5 presents the Trust-Enabling Middleware (TEM) that was developed to provide agents and other applications a platform to exploit the trust metrics described in this work. It allows applications to use their own direct trust metrics with the reputation, and confidence metrics by well defined interfaces. They are general enough to support calculations on agent level, i.e., trust about other agents independent on which nodes they were one, and middleware level, i.e., trust about other nodes. This makes the TEM a suitable platform for trust-enhanced self-properties.

Finally, Chapter 6 concludes this dissertation by discussing the results of the evaluations and presents future work.

2. Organic Computing and Trust Definitions

2.1. Organic Computing

Organic Computing describes a class of systems, where adaptions of the systems are moved from design time to runtime. An OC system self-configures, self-optimizes, self-heals and self-protects autonomously to minimize the need of interventions by an administrator. These properties are called the self-x properties. The self-x properties were first discussed by Horn in the Autonomic Computing Manifest [24] at IBM, introducing the field of Autonomic Computing. Kephart [31] refined the work of Horn, describing the self-x properties in more detail. Autonomic Computing was founded to manage the increasing complexity of modern systems, especially data centers, by introducing self-x properties to these systems.

Organic Computing [44] expanded these ideas to a broader class of systems. Organic Computing aims to enhance complex systems, e.g, middleware systems [58] or traffic light systems [48], with the aforementioned self-x properties. In particular, the effect of emergence is important in the context of Organic Computing. Emergence is a global system property that is a result from the local behavior of its participants. A typical example for an emerging property is the ability of ants to find the shortest path to a food source just by following and emitting pheromones [15]. Every ant decides whether to follow the pheromone trace set by other ants or explore new ways, while emitting pheromones itself. Adding pheromones to an already existing pheromone track intensifies it and increases the chance of other ants to follow this track. The pheromones dilute over time, which results in the shortest path to accumulate higher pheromone levels than longer paths. While only using local rules the ant system in total is able to find the shortest path to a food source without a global entity, which makes this an emergent ability.

The fundamental idea of OC systems is the transfer of decisions from design time to runtime. This allows OC systems to adapt autonomously to a higher variety of situations, because not every situation has to be considered when designing the system. OC systems constantly observe themselves and the environment they are in, identify situations when they enter an unacceptable state and reconfigure themselves to regain an acceptable state. This ability is called the Observer/Controller paradigm [44]. A variant of the Observer-Controller paradigm is the MAPE (*M*onitor, *Analyze*, *P*lan, and *E*xecute) cycle [31] introduced in Autonomic Computing. A system constantly monitors the system state. The collected data are then analyzed to identify unwanted system states. In case one such state occurs, a plan is created to move the system back into an acceptable state, which is then executed.

The OC systems considered in this work are grid systems [17]. A grid system consists of several heterogeneous parts, called nodes, that can communicate with each other. Each node is capable to run several services that provide the functionality of the grid. Some examples of grid systems are described in Section 2.3. A node is typically a single PC that runs a middleware which abstracts the transport layer, which allows the services to send messages to other nodes without the need to know, if the nodes communicate with UDP or TCP. The middleware used in this work is the Trust-Enabling Middleware (TEM) [1], which is described in more detail in Chapter 5. Nodes are heterogeneous, because they have different amounts of resources, e.g., CPU power and memory, and services require different amounts of these resources. These systems are also open, i.e., participants can enter and leave the system at any time. The services on the grid can also be agents, forming a Multi-Agent-System (MAS) [60][61]. An agent can act autonomously, while a service only reacts to incoming requests. Agents are able to collaborate and form communities to improve the system. Figure 2.1 displays a sample network with three TEM nodes and some services on these nodes.

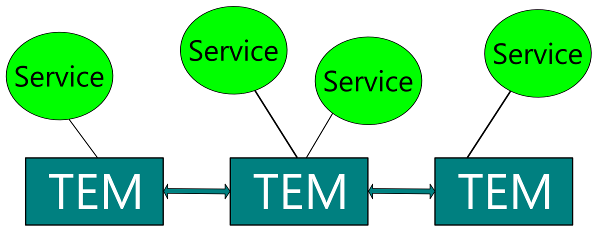


Figure 2.1.: A sample network using the TEM.

The following sections (2.1.1 - 2.1.4) will look at the four self-x properties more closely.

2.1.1. Self-Configuration

A normal system has a configuration defined at design time and starts using this configuration. If such a configuration has to be changed a human typically adjusts the configuration and applies it to the system. A self-configuring system is able to build an initial configuration as well as detect and identify situations requiring a reconfiguration and executing it autonomously. In our grid system, a service has to be assigned or relocated to an appropriate node. The distribution of the services on the nodes form the configuration of the grid. If a new service or node enters the system, a reconfiguration has to be conducted. An appropriate node has to be identified and the service then relocated to it. When a new node enters the system, it may be more appropriate for services than the nodes they are allocated to. This leads to the next self-x property, self-optimization, which chooses the best configuration for a given optimization goal.

2.1.2. Self-Optimization

Self-optimization enables a system to autonomously reach a optimized state, which can vary per application, without the need of a user. A typical optimization for a distributed system is load balancing. Services are distributed in such a way that all nodes are equally loaded. Current self-organization algorithms do either expect their nodes to be reliable or consider only an inevitable decrease of a node's reliability, e.g, a failure due to hardware degregation. In an open system, the reliability of the nodes can fluctuate, i.e., the reliability can increase again. This is the case, when an unstable connection to a node stabilizes again. To create a reliable system out of such unreliable components, the self-organization algorithms need additional information by constantly monitoring the behavior of the nodes in the system. Trust values do provide this information, see Section 2.2.

2.1.3. Self-Healing

A self-healing system is able to react to partial failures, i.e., the failure of a node. It is able to detect such a failure and reorganize itself to compensate it. In a grid, a node may fail and the system is then able to restart all of its services on other nodes. A self-healing algorithm is therefore a reactive algorithm to identify an unwanted or unstable system state and initiate actions to move the system into a stable state again. Taking the trustworthiness of node into account, i.e., its reliability, it is possible to predict upcoming failures when the reliability of a node is dropping, adding a proactive component. In addition, when restarting services from a failed node, these services can be started on a trustworthy node. Otherwise that service might be in need to be restarted again, when the new node itself is unreliable and therefore likely to fail as well.

2.1.4. Self-Protection

A self-protecting system is able to identify attacks on its infrastructure and uses proactive steps to reduce or prevent the impact of such attacks. Since trust evaluates nodes as appropriate interaction partners, an attack on the trust metrics, which result in misleading trust values, can impair the robustness of the system. A trust system therefore has to implement a self-protection mechanism to increase its robustness against such attacks.

2.1.5. Organic Computing Systems

This section presents relevant systems from the field of Organic Computing.

The Artificial Hormone System (AHS) [58] is a middleware inspired by the human hormone system. It distributes tasks on heterogeneous processing elements, e.g., on a processor grid. It uses artificial hormones to find the best suitable processing element (PE) for a given task, including *eager value*, *suppressor*, and *accelerator* hormones. Eager values initially determine the suitability of a PE for a specific task, which is then modified by suppressors that reduce and accelerators that increase its suitability. The application of suppressors and accelerators depends on several factors, e.g, if a group of tasks should be executed in close proximity (accelerators for close PEs, suppressors for far PEs) or if a PE is already loaded with other tasks (suppressors for this PE). Through the hormones the AHS implements self-configuration, self-optimization, and self-healing. Compared to this work, the AHS requires all PEs to be trustworthy to achieve these abilities, i.e., all PEs equally have to work towards the system goal. Otherwise, misleading hormones could be created, potentially destabilizing the system.

Organic Traffic Control [48] adds adaptive behavior to the traffic control of urban road networks. So far, traffic lights are programmed with a fixed-time signal plan that are based on expected and typical traffic. These preset plans can not cope with unforeseen situations, though, including traffic jams or road works. By giving the traffic lights the ability to communicate and observe the current traffic flow, the signal plans can be adjusted with the goal to reduce the number of total stops each vehicle has to take. Additionally, recommendations can be given to the vehicles to choose another path, when an incident, e.g., a traffic jam, has occurred. The approach uses a reinforced learning system (XCS) [59] to adapt to unknown situations at runtime. To achieve these improvements, each participant has to cooperate, especially the recommendations for alternative routes in case of an incident, is based on an assumption of benevolence. If not, malicious recommendations could actually create a traffic jam, which would result in the opposite effect than what was originally intended.

CARISMA [47] is a middleware for embedded distributed systems. It is able to distribute tasks and react to failing nodes or new nodes entering the system. Some of these tasks have real-time constraints [7]. A task with a real-time constraint must finish its work within a specified time span or its result is worthless or may even cause a catastrophic result, e.g, an airbag in a car that did not trigger in time. CARISMA introduces so called *capabilities*, which provide a general description of the abilities of a node and its resources. To support the real-time requirements, CARSIMA expects to run on specialized hardware that provides these real-time capabilities. Here, the collaboration of each node is essential, otherwise a node lying about its capabilities would result in failed deadlines of real-time tasks.

The Self-Organizing Smart Camera System [22][28] consists of a number of cameras with computation power. They communicate and work together to autonomously track persons or groups of persons. They are able to maintain their tracking abilities in case of partial communication failures and can even compensate for cameras that have failed. Due to the processing power of each camera, the required calculations are done distributively, negating a single point of failure. However, the system relies on the correctness of the calculations done by the cameras. If a camera deliberately returns false but plausible results, the information from the system would be compromised, e.g., falsifying statistics or loosing track of a person. This benevolence assumption hinders the approach to be applied in an open system that uses arbitrary but available cameras from unknown sources, when no own cameras are available.

The Organic Middleware OCµ [50] distributes services on a distributed system with the goal to load balance the nodes in the system. It was enhanced with an automated planner [55] to combine the separated self-x properties into an integrated approach. However, in an open system with arbitrary nodes, not every node is equally suited for a service, even if it provides the required resources. Nodes might be unreliable or have malicious intent. The Trust-Enabling Middleware (TEM) presented in this work improves OCµ by integrating the trust metrics. OCµ and TEM are described in more detail in Chapter 5.

2.2. Definition of Trust

As was described in Section 2.1.5, current OC systems assume the benevolence of all participants. Only when every part of the system tries to further the system goal, emergent properties occur. In an open and heterogeneous system, that benevolence assumption must be dropped. In such a system, malicious participants have to be considered, which adds uncertainties and risks. By observing the behavior of the participants, malicious ones can be identified. Trust enables cooperation, when uncertainty and risks exist and is therefore an adequate tool to rate the behavior of an interaction partner and adjust decisions accordingly [54].

By observing the trustworthiness of interaction partners the self-x properties of OC systems can be improved. Services, that are more important, e.g., that are essential for the system, can be assigned to more trustworthy nodes, therefore reducing the chance of their failure. This increases the availability of these services, which increases the overall robustness of the system, since a failure of the important services would have a much higher impact than failing of normal services.

Trust was investigated in several works, Marsh [41] made a thorough review of the literature to trust on philosophy, sociology and psychology and described a first approach to transfer trust into computational systems. Since then more research was conducted to model trust for computational systems, e.g., the FIRE [25] trust framework. An overview of newer trust frameworks is presented in Section 2.4.

Trust is context sensitive, multifaceted and subjective. It is *context specific*, since trust in an interaction partner does not include for all possible interactions, e.g., Alice may trust Bob to drive her safely per car, but not to fly her safely per plane. So Bob is trustworthy in the context as a car driver, but not in the context of a pilot. In an OC system, where a node can have several different services, which may each provide a different capability, the trust value has to be distinguished for each service of a node. In addition, an arbitrary context can be specified for each service.

Trust consists of several *facets*, the following of which were defined by the DFG Research Group 1085 OC-Trust [57]:

Functional correctness: The quality of a system to adhere to its functional specification under the condition that no unexpected disturbances occur in the system's environment.

Safety: The quality of a system to be free of the possibility to enter a state or to create an output that may impose harm to its users, the system itself or parts of it, or to its environment.

Security: The absence of possibilities to defect the system in ways that disclose private information, change or delete data without authorization, or to unlawfully assume the authority to act on behalf of others in the system.

Reliability: The quality of a system to remain available even under disturbances or partial failure for a specified period of time as measured quantitatively by means of guaranteed availability, mean-time between failures, or stochastically defined performance guarantees.

Credibility: The belief in the ability and willingness of a cooperation partner to participate in an interaction in a desirable manner. Also, the ability of a system to communicate with a user consistently and transparently.

Usability: The quality of a system to provide an interface to the user that can be used efficiently, effectively and satisfactorily that in particular incorporates consideration of user control, transparency and privacy.

Trust can either be calculated by a global trust metric or by local trust metrics. An example for a global trust metric would be the eBay reputation metric[1], where all participants write their experiences in a centralized repository and also request trust values from that repository. A local trust metric calculates a trust value locally on each participant of the trust net, without a global entity. Therefore these trust values can vary between different participants, making them *subjective*.

Apart from being context specific and having different facets, trust consists of two aspects: *Direct trust* and *Reputation*.

Direct trust describes the personal experiences one gathers about another, based on interactions with that interaction partner.

Reputation on the other hand describes the experiences of third parties, recommendations based on the information gathered from others, who had direct experiences themselves.

Direct trust is typically preferred over reputation, since using ones own experiences instills more confidence than using the opinions of others. But at times, e.g., when not enough or outdated experiences exist, reputation can be used to complement the own lack of information. Figure 1.1 illustrates how direct trust, reputation and confidence are aggregated to a total trust value. The metrics used for direct trust (Delayed-Ack) and reputation (Neighbor-Trust) are described in Section 3.1 and Section 3.2.

Most trust metrics in this work are generally applicable to all facets. Reputation, confidence and the aggregation work with direct trust values, i.e., they work if a direct trust value can be calculated. The *reliability* of a node indicates its qualification to host important services. A node with a low reliability has a higher chance of failure and is therefore not suitable for important services. The Delayed-Ack algorithm (see Section 3.1) was developed to gauge the reliability of a node. Reliability trust values are best suited for trust-enhanced self-x properties. The *credibility* rates the ability of a service to deliver what it promised. When working with a service, a specific performance is expected from that interaction, e.g., based on the interface description or a Quality of Service promise. An interaction that fulfills that promise increases the credibility of a service, and problems with the interaction lowers it. This information is crucial for applications to decide which service to interact with. The decision whether a service provided a satisfactory interaction, can only be done by the application. The applications developed in the OC-Trust project use trust of the facet credibility. Besides Delayed-Ack to calculate reliability on middleware level, algorithms to gather reputation (Section 3.2), confidence (Section 3.3) and an aggregation of these values (Section 3.4) are presented in this work. They are suitable to be used with any kind of direct trust of every facet. Overall these facets are based on the behavior of interaction partners and

[1]http://pages.ebay.com/help/feedback/scores-reputation.html

have to be calculated at runtime.

Trust values can be defined in one of the following domains:

1. A discrete number of possible values. One example is the eBay trust metric with three values: positive, neutral and negative. Another is the rating system of Amazon, which has five values, 1 to 5 stars.
2. A real number between 0 and 1.
3. A real number between -1 and 1.

Variant (1) is typically used for humans, since humans can handle discrete values better than continuous ones and also prefer natural numbers [21]. However, real numbers allow for a more detailed evaluation of an interaction partner's trustworthiness. Especially some applications, e.g., the EnergyGrid described in Section 2.3, even require trust values based on real instead of discrete numbers for a sensible trust estimation. Therefore, trust metrics used in artificial societies or computation systems are typically based on real numbers.

The scale of [-1;1] explicitly models distrust. A trust value of 0 stands for indifference, i.e., no knowledge about the trustworthiness of the interaction partner is known. -1 stands for complete distrust, i.e., one is sure that the interaction partner is not trustworthy, whereas 1 stands for complete trust, i.e., one is sure that the interaction partner is completely trustworthy. The corresponding trust metrics have to consider the effect of negative numbers in their calculations. This leads to a different kind of metric compared to the [0;1] interval.

Whether there is a difference and what that difference is between these two domains is still debated in current literature [63]. Mathematically both domains can be converted into each other, but one can argue, that distrust is semantically different from having no trust. Also, if distrust is the opposite of complete trust is still open to debate. The metrics presented in this work use the [0:1] scale, because the goal is to always find the most trustworthy interaction partner. Adding explicit distrust would not increase information value, since an untrustworthy interaction partner is equally unqualified as an distrusted interaction partner. In this interval a value of 0 represents complete untrustworthiness, whereas 1 stands for complete trustworthiness. 0.5 here can be seen as an indifferent opinion about the trustworthiness of the interaction partner.

2.3. Application Scenarios

Within the OC-Trust Research Group, several application scenarios for trust in OC systems are presented.

Our current energy grid is supplied by an increasing number of different power plants, which have either a deterministic or stochastic energy production. Deterministic power plants can adjust their energy production, e.g., coal or atomic power plants. The energy production of stochastic power plants is not controllable, it is dependent on the environment, e.g., solar power plants produce energy in relation to the current level of solar radiation, or wind power plants depend on the strength of the wind. In recent years, the amount of stochastic power plants has increased, particularly since they do not consume fossil fuel. The European Union published its goal to further regenerative energy sources [2] which will increase the amount of stochastic power plants by an even greater amount in the near future.

This poses a significant challenge for the future structure of the energy grid. It is based on the fact, that the same amount of energy is produced and consumed. With an increase of stochastic power plants, the regulation of the energy grid to maintain this equilibrium will be increasingly difficult, exceeding the possibility of the manual regulation of today. For an automatic regulation, the power production of the stochastic power plants needs to be predicted, e.g, by using the weather forecast, so that the deterministic power plants can be regulated as needed. By integrating trust, the trustworthiness of the predictions can be measured. This allows a self-organizing system of *Autonomous Virtual Power Plants (AVPPs)* [56] that group together small power plants with accurate and non accurate power predictions. Grouping trustworthy and untrustworthy power plants together to an AVPP prevents the possibility of a cumulative divergence of the energy production of several untrustworthy power plants at once that might prevent a timely reaction. AVPPs also reduce the complexity to calculate plans for the deterministic power plants to balance the variable output of the stochastic power plants, since these plans need only be calculated per AVPP instead of the entire energy grid. Trust is therefore a way to cope with the upcoming uncertainties of the future energy grid, when a high number of power plants are of a stochastic nature.

Another example of an application that profits from the inclusion of trust is an open computing grid. Such a grid provides high parallel computation power for applications that profit from it, e.g., face recognition [6] or ray tracing [19]. However, not every member of the grid is equally interested and able to perform computational tasks for other members. For example, some members might want to exploit the grid by only sending and rejecting every task from others, so called *FreeRiders* [4]. By introducing trust, the members can identify those malicious nodes and form *Trusted Communities* (TCs) [37]. The members of a TC know each other to be trustworthy, which reduces the risk for each member to receive unsatisfactory work. By continuous observation of the behavior of the members of a trusted community, members can be excluded if their behavior changes. The other way is also possible, a so far untrustworthy participant can

[2]http://ec.europa.eu/clima/policies/package/

regain its trustworthiness and rejoin a trusted community, if it acts accordingly. This reduces the need to distribute redundant tasks to cope for untrustworthy nodes in the computing grid, increasing its throughput.

2.4. Trust Metrics in Literature

There exists a wide variety of literature about trust. Several researchers in the fields of psychology, sociology and philosophy researched trust and presented several definitions, what trust actually is [14][38][18]. Marsh [41] conducted an extensive survey of that literature and presented a first approach to translate trust to a computational system. Since then, several metrics and trust frameworks have emerged to formulate trust in a way, that computers can calculate.

A lot of metrics concentrate on reputation, based on direct trust entries of humans, e.g., rating systems of websites like eBay[3] or Amazon. Likewise the Google PageRank algorithm [5] exploits the connectivity of websites to identify highly frequented websites, which can be compared to reputation, since linking to another website illustrates a positive reference to that website. The algorithm was enhanced since then to prevent spamming, but in its basis it provided superior search results compared to other search engines. Another example is the Web of Trust (WoT) [11], which uses real life meetings between persons to verify the identity of someone. Given enough confirmations, the identity of a person is considered valid. All of these metrics are *global* reputation metrics. A global reputation metric saves its information at a central space, that all other participants can request information from. In comparison a local reputation metric is based on local information of each participant, i.e., for each reputation request appropriate information has to be gathered from all relevant participants, which can contribute with their own experiences. Several local reputation metrics, e.g., TidalTrust[21] and MoleTrust [42], ask known interaction partners for information (called neighbors), which in turn ask their neighbors until they reach someone with direct experiences or the path gets too long. The longer the path, the lower the value of the information (similar to the information someones gets from a friend, who gots it from a friend and so on).

Kamvar et al. present EigenTrust [30], a reputation metric for P2P networks with the goal to minimize the amount of broken files a participant gets through malicious peers. They rate the integrity of a file, i.e., is it working and correct, and this way identify peers, which inject broken files into the network. The biggest difference to the reputation metric presented in this work lies in their assumption that the ability of a peer to provide good files is equivalent to its ability to provide good information about others. Marmól and Peréz [39] demonstrated some problems with this assumption, leaving the

[3]http://pages.ebay.com/help/feedback/scores-reputation.html

metric vulnerable for certain kinds of attacks. The Neighbor-Trust metric in this work explicitly separates these two. They also assume that trust is transitive, which is not necessarily true. The question whether trust should be assumed to be transitive or not is an ongoing debate [12][21].

SPORAS [62] is yet another reputation metric. Its focus is to prevent entities to leave and rejoin the network to reset possible bad reputation values. Compared to Neighbor-Trust, SPORAS does not assign different values for the reputation value provided by another entity and the trustworthiness of that entity to give accurate reputation data. The trustworthiness is calculated from its reputation value. Neighbor-Trust differentiates between these values by defining separate weights; Mármol and Pérez [39] have shown the importance to do this.

FIRE [26] is a trust framework combining direct trust and reputation (called *witness reputation* in FIRE). In addition, it adds the trust parts of *certified trust* and *role-based trust*. Certified trust describes past experiences others had with an agent, who can present it as reference of his past interactions. Role-based trust stands for generic behavior of agents within a role and the underlying rules are handcrafted by users. The four parts are then aggregated with a weighted mean, whereas the weights are adjusted by a user depending on the current system. In comparison, the metrics described in this work do not require user hand-crafted parts like the role-based trust of FIRE and are therefore able to run in a fully automated environment.

ReGreT [51][52] is a trust framework providing similar metrics for direct trust, reputation, and aggregation to the metrics described in this work. Some differences yet exist. The age of experiences is part of the direct trust calculation whereas the trust metrics described in this work consider the age, number and variance as part of the confidence. ReGreT describes a similar metric, which is called the *reliability of the trust value* instead of confidence. Additionally, the formulas for the confidence metrics used in this work are parametrized. Similarly, the reputation metric can be parametrized to define the threshold, when one's own experiences are close enough to the reputation data given by a neighbor (called a *witness* in ReGreT). Also instead of directly using the confidence for the aggregation of direct trust and reputation a weight is calculated by a parameterizable function using the confidence. One of the major differences though lies in the evaluation. While ReGreT works in a scenario with fixed agent behavior the evaluation in this work investigates systems with varying agent behavior, where a very trustworthy agent can change to the direct opposite. Several such changes per scenario are considered. Bernard et al. [3], e.g., describe a system with such adaptive agents.

3. Trust Metrics

When calculating trust in a distributed systems, there are generally two facets to look at:

1. To measure the **Reliability** of a node or service, i.e., its ability to process incoming requests or availability.
2. To measure the **Credibility** of a node or service, i.e., its ability to deliver, what it promised to do.

To calculate a trust value for any of these facets, the following steps are required:

1. Gathering experiences by interacting with another node or system.
2. Evaluate these experiences and assign a value between 0 and 1, with 0 for the worst possible experience and 1 for the best possible experience.
3. Calculate a trust value from these evaluated experiences using appropriate trust metrics.

To be able to calculate the credibility of an interaction partner, the semantics of the transaction have to be known, i.e., item 2 requires the evaluator to know, what the transaction was about to be able to measure its correctness. On middleware level this is not possible, since the middleware does not know about the semantics of the messages sent to other services, therefore the credibility of services is impossible to calculate. The applications that issued the transaction are able to do these measurements, though. The credibility of a node would measure the correctness of its basic functions, i.e., if a service relocation was successful or a message was delivered to the correct services. The Trust-Enabling Middleware (TEM) was created to provide these functionality as well as trust capabilities, see chapter 5. We therefore assume that all basic operations of the middleware are executed correctly, regarding its credibility.

In comparison the reliability of a node can be measured without the need to interpret the semantics of application messages. By observing the message flow to other nodes, dropped messages can be identified and the availability of a node in a given time can be determined. The middleware can provide this information to all of its running services to give them additional information to decide, with which other application to interact with. The middleware itself can exploit this information to improve the self-x properties to create a more robust service distribution and react on changes in the environment that reduces the reliability of a node. Section 3.1 presents the Delayed-Ack algorithm [35][36] that identifies lost messages and calculates a direct trust value from it.

Section 3.2 presents the Neighbor-Trust metric [33], a metric to calculate reputation that is able to identify lying nodes and adjust its reputation calculation to only include trustworthy nodes. Section 3.3 shows, how the accuracy of the calculated direct trust can be measured by determining the confidence in these trust values [32]. Finally section 3.4 presents a metric to calculate a total trust value out of direct trust and reputation using confidence to weight both parts for the total value [34]. All of these metrics do not require the Delayed-Ack algorithm as direct trust metric, but work with any type of direct trust metric and every facet. This allows the applications running on the middleware to exploit these metrics based on their own direct trust metrics, leading to a generic approach for calculating trust in a distributed system. The implementation of these metrics into the TEM are described in chapter 5.

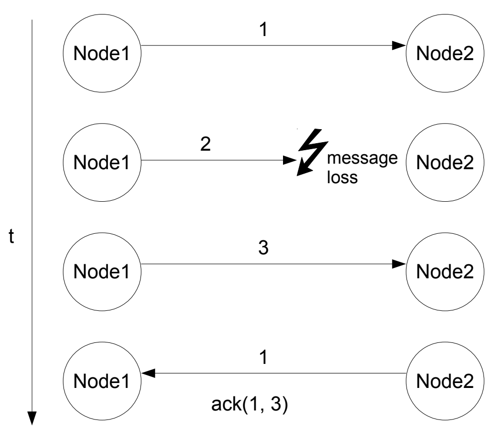
3.1. Direct Trust

The reliability of a node is an important basis for all interactions executed on the system. If a node is not reliable, i.e., it cannot be reached due to a high rate of lost messages, the applications on it can be as good as they will, their calculations are unable to reach their interaction partner or only with a lot of delay due to error corrections. For the self-x properties the reliability has also to be considered to assign those services that are essential for the structural integrity of the system only to highly reliable nodes. It also allows for a more robust failure detection, where the chance of all observers of a node failing simultaneously is minimized. Due to these reasons the Delayed-Ack algorithm was developed to measure the reliability of a node by observing the message flow between nodes and identifying lost messages.

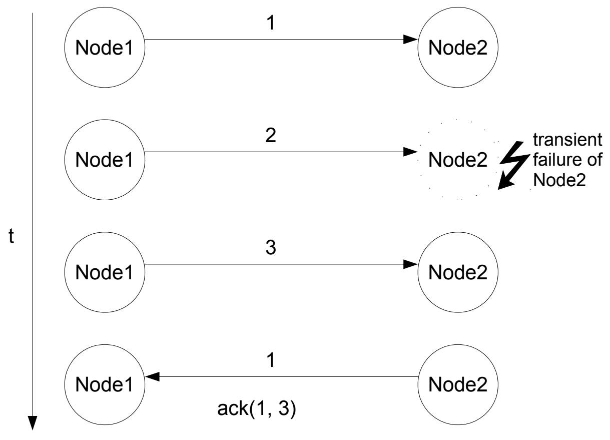
3.1.1. Delayed-Ack Algorithm

The Delayed-Ack algorithm observes the message flow on middleware level. This especially means that no knowledge from the underlying transport layer need to be considered. While TCP has error corrections, message loss can be expected by using UDP. Loosing a message can have two reasons:

- The message is lost on its way to the node, see Figure 3.1(a) or
- the message is lost because the target node has failed, see Figure 3.1(b).



(a) Loss of a message in transit.



(b) Loss of a message due to failed node.

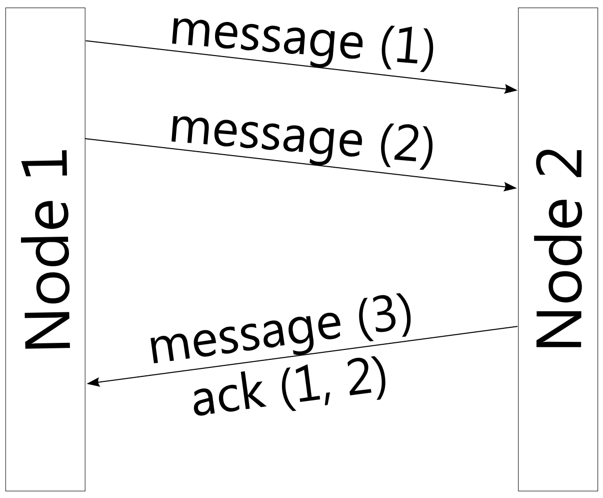


Figure 3.1.: The Delayed-Ack algorithm

Both variants result in problems to reach the node, reducing its reliability, and are therefore handled equally. If an distinction has to be made, additional knowledge must be taken from the underlying transport layer. When measuring the amount of lost messages, the reliability of a node can be determined. A high number of lost messages indicates, that communication with that node is impaired and therefore extra care and additional error corrections are required to communicate with services on this node.

To measure if a message was lost, a unique ascending message number is added to each message. This number will get acknowledged by the interaction partner and the acknowledgment is sent back as piggy-back as well. Every message therefore contains acknowledgments for every received message since the last time a message was sent. Figure 3.1 depicts the use of these message numbers.

In total every *sent* message contains:

- A unique ascending message number
- A list of acknowledgments, acknowledging all messages received since the last time a message was sent.

The received acknowledgments are then compared to the list of sent message numbers. In case of message numbers that are not acknowledged, so called gaps, the message is considered lost, resulting in a negative experience (0). Acknowledged message numbers result in a positive experience (1). If messages do not get acknowledged after a set amount of time, a negative experience (0) is saved. This allows for an increase in negative experiences over time, after a node failed and stopped sending message, and therefore is not generating any more gaps. If an acknowledgment is received after the message was already set as not received, the experience is retroactively changed to a positive value (1).

A potential problem with the Delayed-Ack algorithm occurs, when a node rates the reliability of a communication partner but is unreliable itself. Let *node1* be the unreliable node and *node2* its interaction partner, then the following case can occur:

1. *Node1* sends some messages to *node2*.
2. *Node2* receives the messages and responds later, adding the acknowledgments for the received messages.
3. *Node1* on the other hand now looses the messages sent by *node2* with the added acknowledgment due to a transient failure of *node1*.
4. *Node1* will now rate *node2's* reliability down because it believes node2 to have lost the original messages while node1 lost the message with the acknowledgment instead.

Figure 3.2 depicts the loss of a message, which would acknowledge three messages sent by node1.

In this case a node unjustifiable rates down the reliability of interaction partners because of its own bad reliability. Evaluations have shown that the calculated trust value t_n for node n in this case results in

$$t_n = t(self) \cdot t(real)_n$$

where $t(self)$ denotes the reliability value of the node, which is rating the node n, and $t(real)_n$ denotes the trust value of the node n, if the observing node would be completely reliable and not loose some messages itself.

To counter this effect the Delayed-Ack algorithm[35] was improved to the Enhanced Delayed-Ack [36] algorithm. The basic idea is to resend acknowledgments until it is certain at least one message with this acknowledgment is received. This is archived

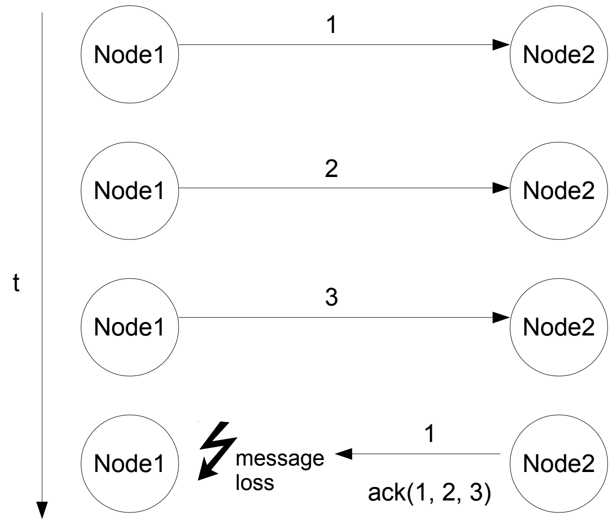


Figure 3.2.: Loss of a message with a piggy-backed ack

when at least one of these messages itself are acknowledged. After that this specific acknowledgment does not have to be resent anymore. When a node is highly unreliable itself, it will eventually gain an appropriate estimation of the reliability of its interaction partner regardless of its own reliability. In this case a metric that rates older values higher than newer values is preferable, because older values actually depict the real reliability value of the interaction partner whereas newer values most likely are timed out negative experiences due to lost messages with acknowledgments.

Based on these experiences a trust value for reliability t_r can be calculated. For this calculation several metrics were examined, with n the amount of messages, ordered by the time of their occurrence and x_i the experience of the interaction (1 for a positive experience, 0 for a negative experience):

1. arithmetic mean: $t_r = \frac{1}{n}\sum_{i=1}^{n} x_i$
2. time weighted mean: $t_r = \frac{\sum_{i=1}^{n} \frac{i}{n} x_i}{\sum_{i=1}^{n} \frac{i}{n}} = \frac{\frac{1}{n}\sum_{i=1}^{n} i\ x_i}{\frac{n+1}{2}}$
3. inverted time weighted mean: $t_r = \frac{\sum_{i=1}^{n} \frac{n-i}{n} x_i}{\sum_{i=1}^{n} \frac{n-i}{n}} = \frac{\sum_{i=1}^{n} (n-i)\ x_i}{\sum_{i=1}^{n} (n-i)}$

(1) is a simple mean metric. (2) and (3) are a weighted mean metric that weight the experiences based on the time they occurred. (2) weights newer experiences higher whereas (3) weights older experiences higher. On first glance (3) does not look like a reasonable metric considering the higher expressiveness of more current experiences. In case of an interaction partner with consistent, but fluctuating, behavior, weighting older experiences higher results in a trust value with less fluctuation. Such a behavior is a result of an interaction partner with a specific reliability value but with a high variance around it, e.g., 20% of messages are lost by an interaction partner based on an

observation of lost (0.0) and received (1.0) messages. A mean value will average these losses to a reliability value of 0.8 (loss of 20% messages), but new experiences of 1.0 or 0.0 will create a high fluctuation around the mean value especially if current experiences are weighted high. This effect is diminished by rating old experiences higher.

3.1.2. Evaluation

To evaluate the Delayed-Ack algorithm it is analyzed with respect to its convergence speed towards a fixed real trust value. Every node has a specific fixed trust value p. Such a node will react to messages with a probability of (1-p). So if the node's real fixed trust value is 0.9, 10% of the messages are lost and therefore not acknowledged. In the evaluation the sought reliability value of that node is therefore 0.9. The evaluation analyzes the amount of interactions needed for the algorithms to converge on the real trust values as well as how much impact bad reliability of an observer has on its observing capabilities.

To accomplish this, a network of 30 nodes is used with the following configuration:

- Ten nodes with 100% reliability,
- ten nodes with 90% reliability, and
- ten nodes with 50% reliability.

A node with a reliability value of less than 100% only receives messages with the given percentage, be it because of transient node failures or actual message loss. A node picks two random nodes as communication partners at every time step and sends a message to them. The corresponding nodes reply with 75% probability. This should picture a real world system where applications send requests to other applications on other nodes but not always expect a reply, e.g., when a simple information message is sent. The chosen percentages stand for perfect nodes (100%), slightly unreliable nodes (90%), as well as very unreliable nodes (50%) and should represent typical nodes within a network. Ten nodes of every type were chosen to get a variety of results due to the randomness of the message loss probabilities and averaged results. The very low reliability of the nodes, especially a 50% message loss, were chosen to demonstrate the robustness of the algorithm in systems with very unreliable components.

Figure 3.3 shows the average result of all nodes with 100% probability observing the nodes with 50% probability. After some interactions the observed trust value stabilizes around the real trust value. The Delayed-Ack algorithm gauged the trust of other nodes successfully.

On the other hand if the observing node itself is unreliable it gets a biased view on other nodes, demonstrated by Figure 3.4. This scenario is similar to the aforementioned, but

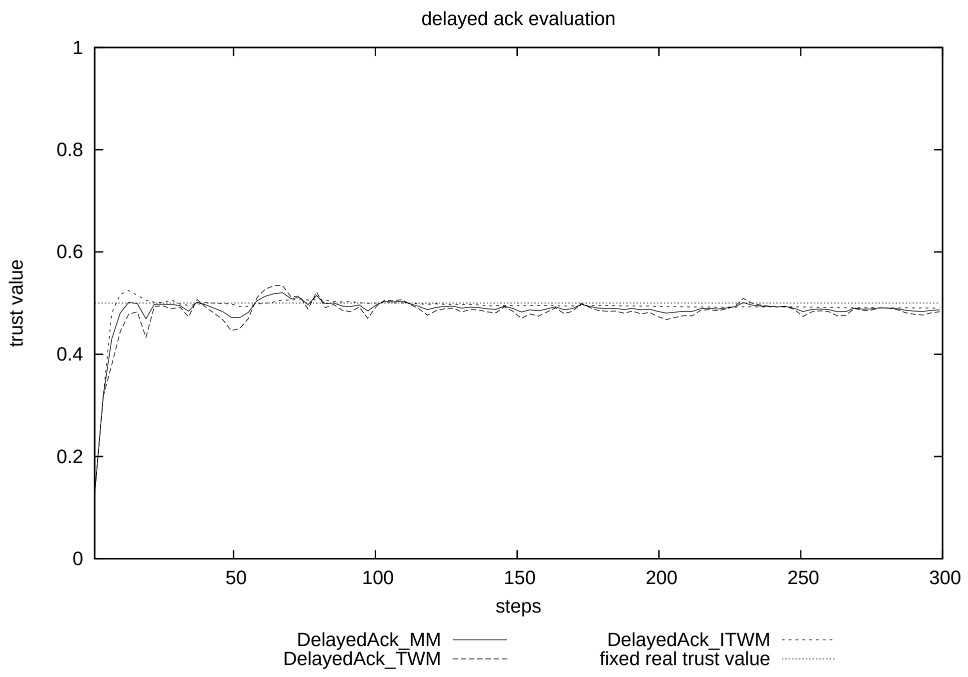


Figure 3.3.: Enhanced Delayed-Ack: 100% reliable node observing another 50% reliable node

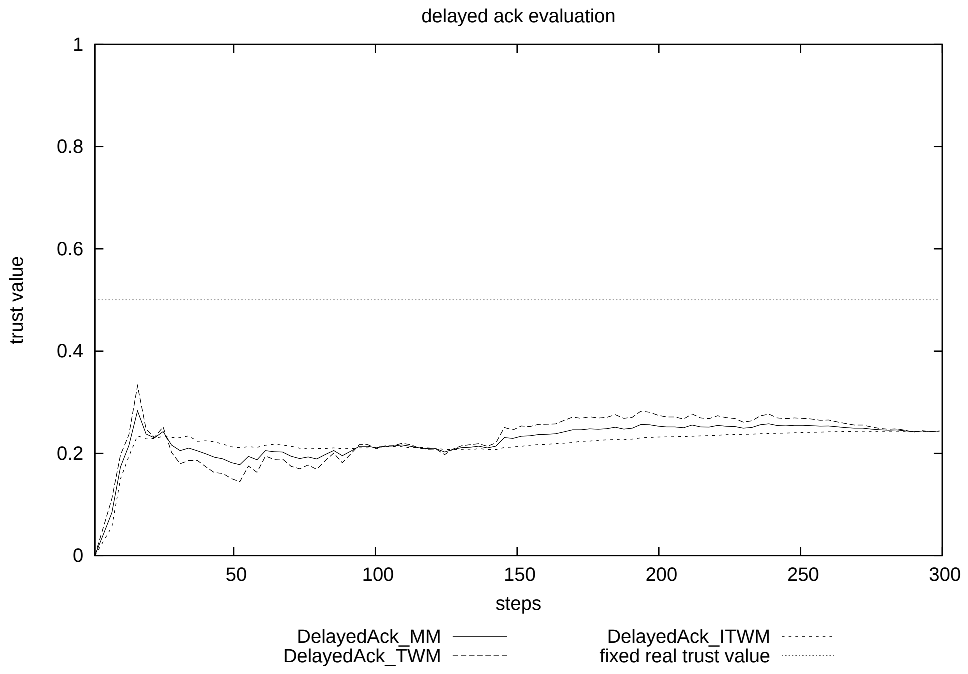


Figure 3.4.: Enhanced Delayed-Ack: 50% reliable node observing another 50% reliable node

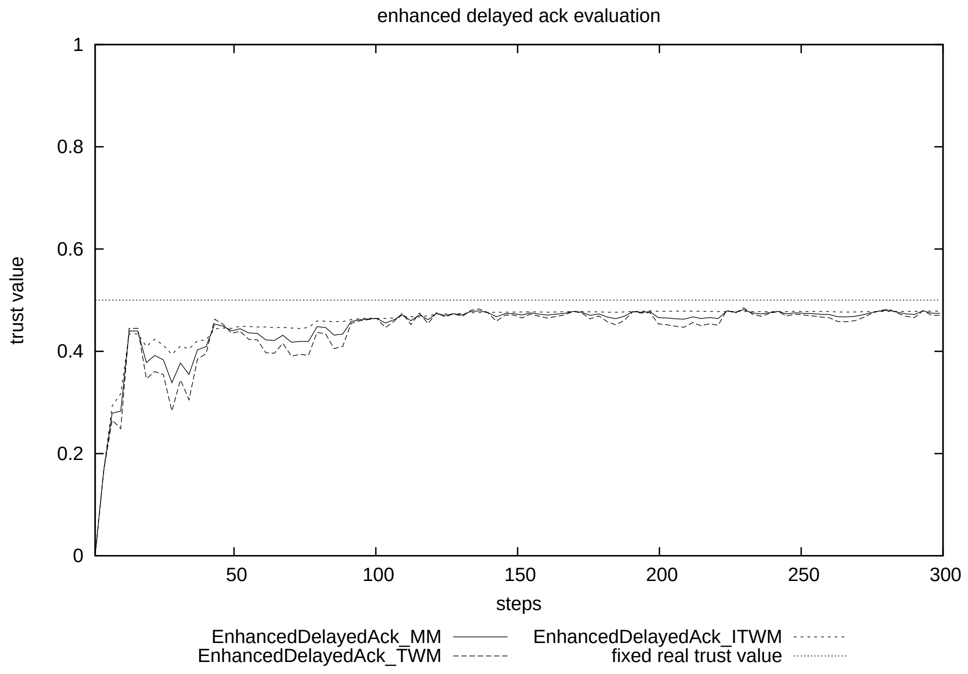


Figure 3.5.: Enhanced Delayed-Ack: 50% reliable node observing another 50% reliable node

this time the observing node has a 50% reliability instead of 100%. As can be seen, the observed trust value stabilizes but at a far lower value than the real trust value. This happens due to additional message losses caused by the observing node. Not only are message lost that were sent to the interaction partner but also the messages coming from this interaction partner, probably containing acknowledgments of actually received messages. Losing these messages and therefore rightly sent acknowledgments marks these message incorrectly as not received. In total the observed trust value is close to 0.25, which is the product of the reliability of both nodes.

In contrast Figure 3.5 shows the same situation, nodes with 50% reliability observing nodes with 50% reliability, with the use of the Enhanced Delayed-Ack algorithm. Compared to Delayed-Ack the observing node gets a quite correct impression of the observed node, regardless of its own unreliable state.

3.2. Reputation

While direct trust gives a good estimation of an interaction partner's behavior, it is not always available. Especially when a new node enters the system, it does not know anything about the system yet. Additionally it's behavior itself is not known to any node in the network. The network on the one hand has no choice but to build experiences with the new participating node by conduction transactions with it. The new node on

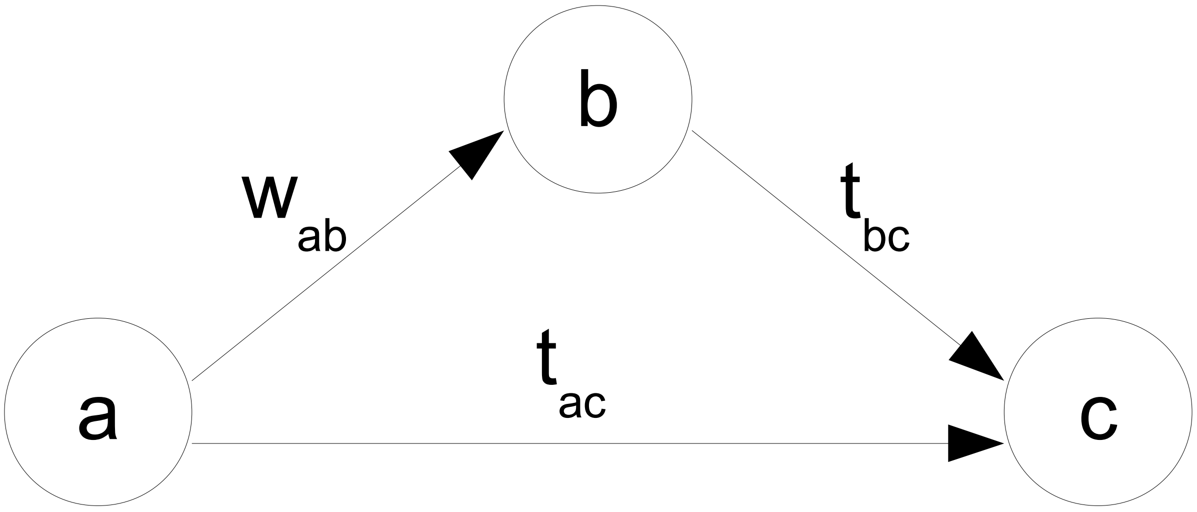


Figure 3.6.: Nodes in the reputation graph

the other hand can exploit the knowledge of the nodes in the network, that already accumulated experiences with each other until it has enough own experiences itself. These indirect experiences from third parties are called reputation.

3.2.1. Neighbor-Trust Algorithm

To measure reputation the Neighbor-Trust Algorithm [33] is introduced. It is based on metric 2 presented by Satzger et al. [53], which gathers the direct trust information of all neighbors of the target node. Neighbors in this context describes all nodes that have direct trust information about the interaction partner. Satzger et al. calculated a mean value of the direct trust values of the neighbors. The Neighbor-Trust Algorithm enhances the metric to a weighted mean, where the weights are adjusted over time to consider only neighbors that had similar experiences than oneself, thereby introducing a learning component. Figure 3.6 shows a short example of a network and the neighborhood relationships.

Alice (a) wants to get information about Carol (c), so she asks Bob (b) about his opinion about Carol. w_{ab} is the trust Alice gives the information Bob provides respectively the weight she gives his information and t_{bc} is the direct trust value Bob has about Carol. Later Alice might have a direct experience with Carol, displayed by t_{ac}. To get an accurate value, Alice will ask more entities than just Bob. She will ask all neighbors ($i \in neighbors(c)$) of Carol.

The reputation r_{ab}, i.e., the reputation a gathered about b by collecting information about b from its neighbors ($i \in neighbors(c)$), is calculated with the following formula:

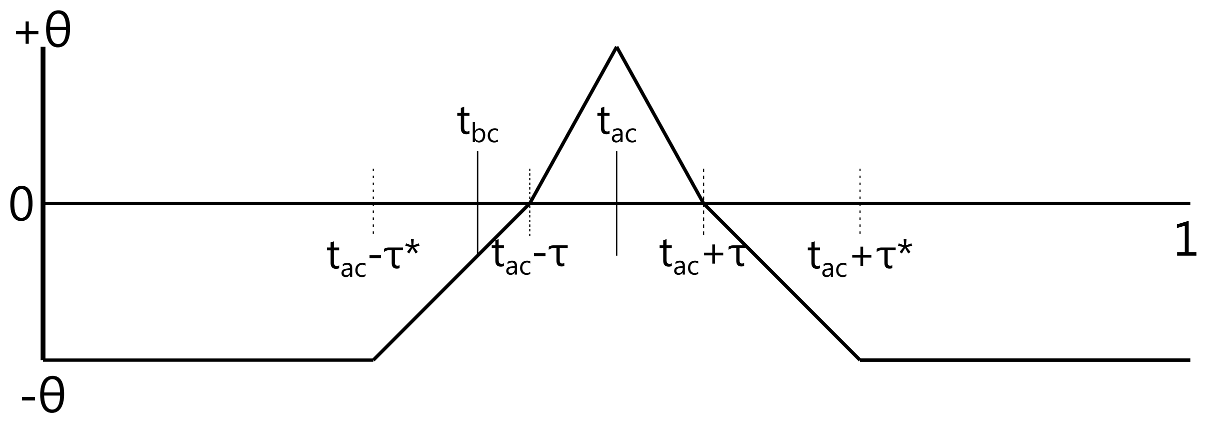


Figure 3.7.: Characteristics of the weight adjustment function of the neighbor-trust reputation metric

$$r_{ac} = \frac{\sum_{i \in neighbors(c)} w_{ai} \cdot t_{ic}}{\sum_{i \in neighbors(c)} w_{ai}}$$

The learning component is the weight w_{ai}. This weight will be adjusted over time, depending how similar the trust values from the neighbors correlate with the node's own experience. If an experience is close enough to the information given by a neighbor, its weight will be increased and further information will be rated higher. Then again, if the discrepancy is too high the weight will be reduced and therefore further information of this neighbor will be rated down. This creates a group of neighbors that had similar experiences than the asking node. Golbeck [20] showed with a movie review platform enhanced with a social network, that getting reviews from users preferring similar movies yielded better information than getting the global mean. Not only does the Neighbor-Trust Algorithm provide this functionality, but it also excludes nodes that provide false information purposely.

Figure 3.7 shows the characteristics of the weight adjustment function:

w will only be adjusted within a *maximal adjustment* θ, thus preventing a too excessive change of w through a single transaction. Furthermore, two thresholds are defined:

- τ: Up to this threshold the experiences of the neighbor and one's own are close enough to increase the weight to this neighbor. More precisely the obtained trust value from the neighbor t_{bc} lies within the own direct trust value $t_{ac} \pm \tau$.
- τ^*: Up to τ^* but beyond τ the difference between the received trust value of the neighbor t_{bc} and one's own trust value t_{ab} is too high, therefore w is decreased. Beyond that w is reduced fully by θ.

In total the formula for the Neighbor-Trust metric is as follows:

$$w_{ab}^{n+1} = w_{ab}^{n} \begin{cases} +(\frac{\tau - |t_{ac}^n - t_{bc}^n|}{\tau}) \cdot \theta, & \text{if } 0 \leq |t_{ac}^n - t_{bc}^n| \leq \tau \\ -(\frac{|t_{ac}^n - t_{bc}^n| - \tau}{\tau^* - \tau}) \cdot \theta, & \text{if } \tau < |t_{ac}^n - t_{bc}^n| \leq \tau^* \\ -\theta, & \text{otherwise} \end{cases}$$

3.2.2. Evaluation

To evaluate the Neighbor-Trust metric a network of 10 nodes with different percentages of lying (malicious) nodes was used. The relatively small number 10 was chosen to identify specific effects that are presented further down. Simulations with more nodes yielded similar results. A node is malicious if it returns a reputation value that does not match its actual experiences, i.e., it is lying about other nodes. In the case of this simulation the malicious nodes always return a reputation value of 0, regardless of previous experiences. By doing this, they try to denunciate all other nodes to push their own reputation value compared to the others. The malicious nodes themselves return always wrong results if interacted with. The simulation was conducted in timesteps. In every timestep every node chose an interaction partner based on their reputation values, whereas the node with the highest reputation value was chosen. In case of a draw, one of the nodes with the highest reputation rating was chosen randomly. Especially at the start of the evaluation, when no reputation value is known yet, a random node is chosen for the first interaction. Apart from the first interaction, a value has to be defined for nodes, which were not interacted with yet and therefore no information about them exist so far. An arbitrary starting value has to be assigned to such a node to be able to compare it to the others. The simulation will show the effect for different initial values.

To show the results, the nodes were categorized in two types: honest and malicious nodes. For each time step the average reputation value of the honest nodes about the two types are displayed as well as the weight the honest nodes have about both types. The weight represents the honesty the corresponding nodes have about relaying their direct experiences.

Figure 3.8 displays the results for a network with 30% malicious nodes. Mainly two things can be seen here. In the start, the honest nodes get wrong reputation data about other honest nodes due to the false information of the malicious nodes. Over time the malicious nodes are identified as such, which can be seen by the decreasing weight the honest nodes have about the malicious nodes. Simultaneously the reputation of the honest nodes increases as the weight of the malicious nodes drops. After about 20 interactions all malicious nodes are identified as such and have their weights set to 0. Therefore their reputation data is removed from the calculation and does not influence it anymore.

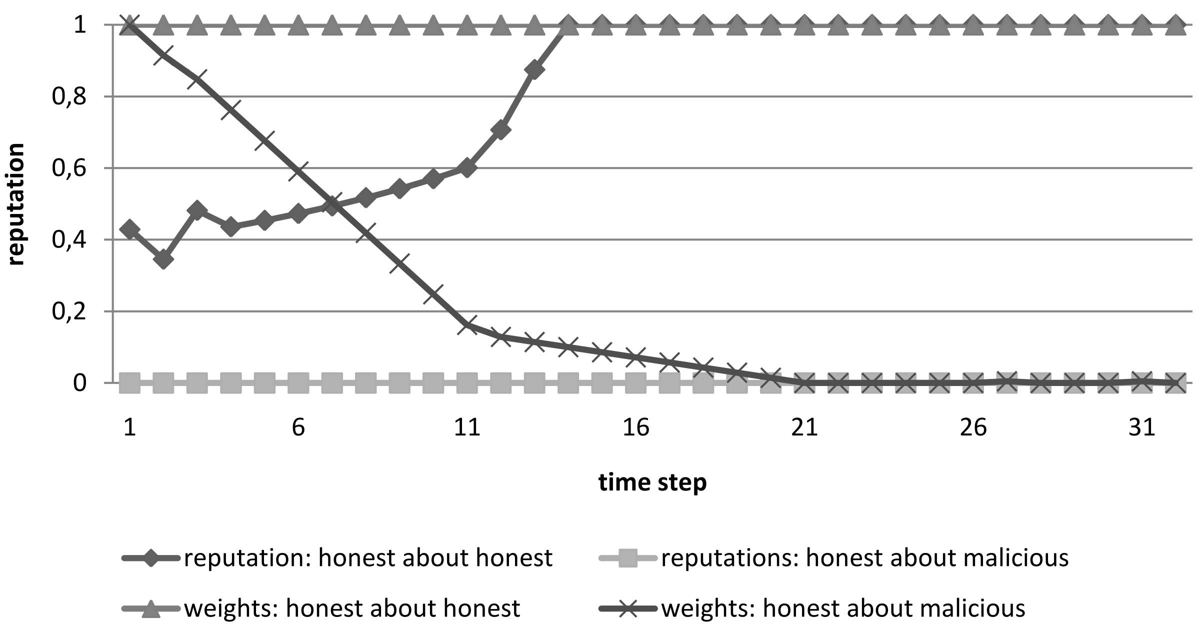


Figure 3.8.: Reputation in a network with 30% malicious nodes

Apart from that the weight of honest nodes about the other honest nodes starts and ends at 1: Telling the truth, their weight never gets reduced. The same happens with the reputation data of the honest nodes about the malicious nodes. Since they never lie, they always rely their bad experiences about the malicious nodes.

In Figure 3.9 the amount of malicious nodes was increased to 50%. The results are similar to 30%. Even increasing the amount of malicious nodes to 70%, as can be seen in Figure 3.10, results in a stable system. This demonstrates the robustness of the Neighbor-Trust metric, as it returns meaningful results, even if the amount of malicious nodes exceeds 50% of the total nodes.

In the three scenarios above the threshold for unknown nodes was set to 0, i.e., if no reputation data was available for a node a start value of 0 was assumed. This can be seen as a pessimistic approach [40]. In Figure 3.11 the threshold was changed to 0.5, i.e., a node with no reputation data starts with 0.5. Similar to the above scenarios the honest nodes identified the malicious nodes resulting in a final reputation value of 1 for other honest nodes.

Compared to the other scenarios the average weight value stabilizes on a value above 0. Since this value is an average value, not all weights of honest nodes about malicious nodes are set to 0. In this case a switch to another interaction partner occurred after its reputation dropped below 0.5, the threshold for an unknown node. In the end the malicious nodes and the honest nodes interacted with a different set of nodes. From the point of view of an honest node, some of its final interaction partners never interacted

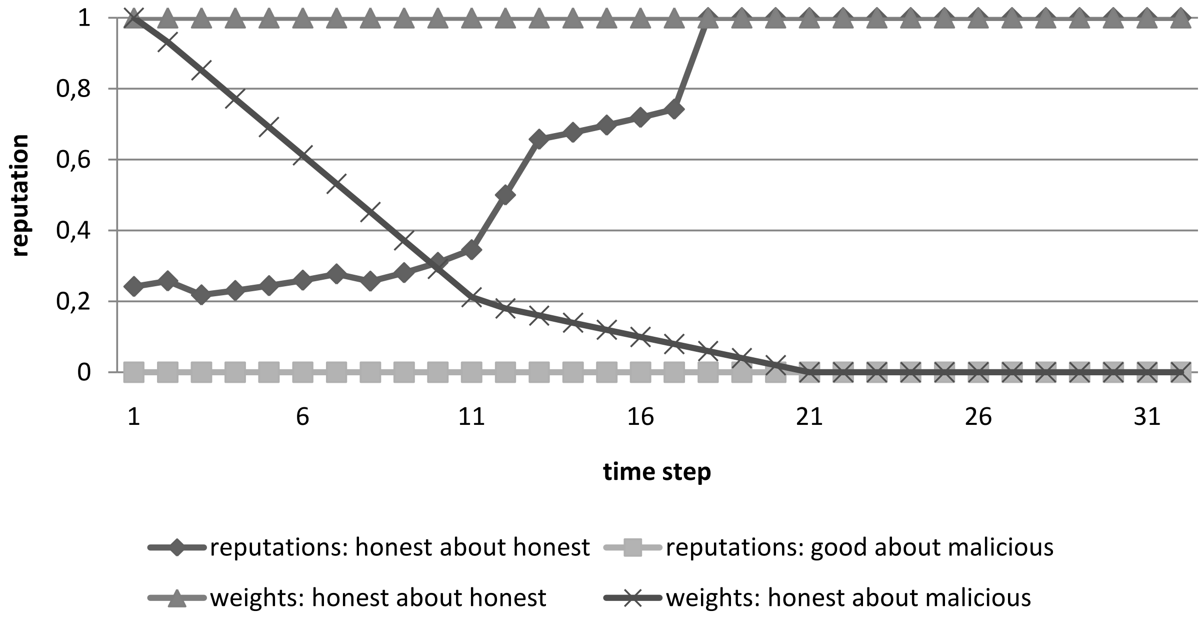


Figure 3.9.: Reputation in a network with 50% malicious nodes

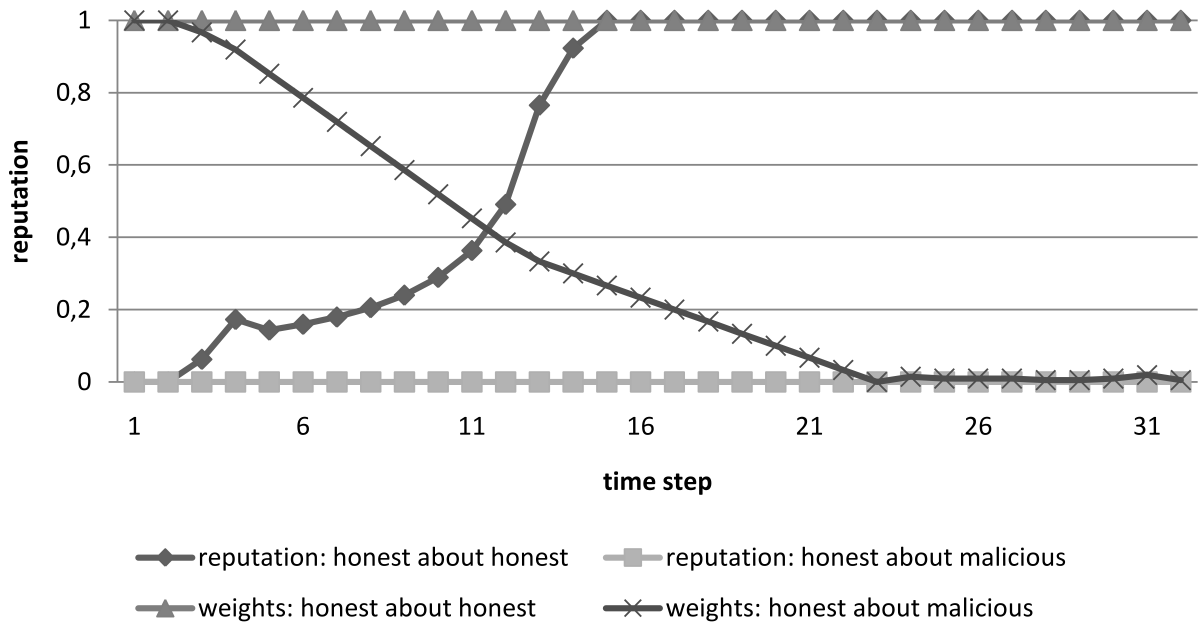


Figure 3.10.: Reputation in a network with 70% malicious nodes

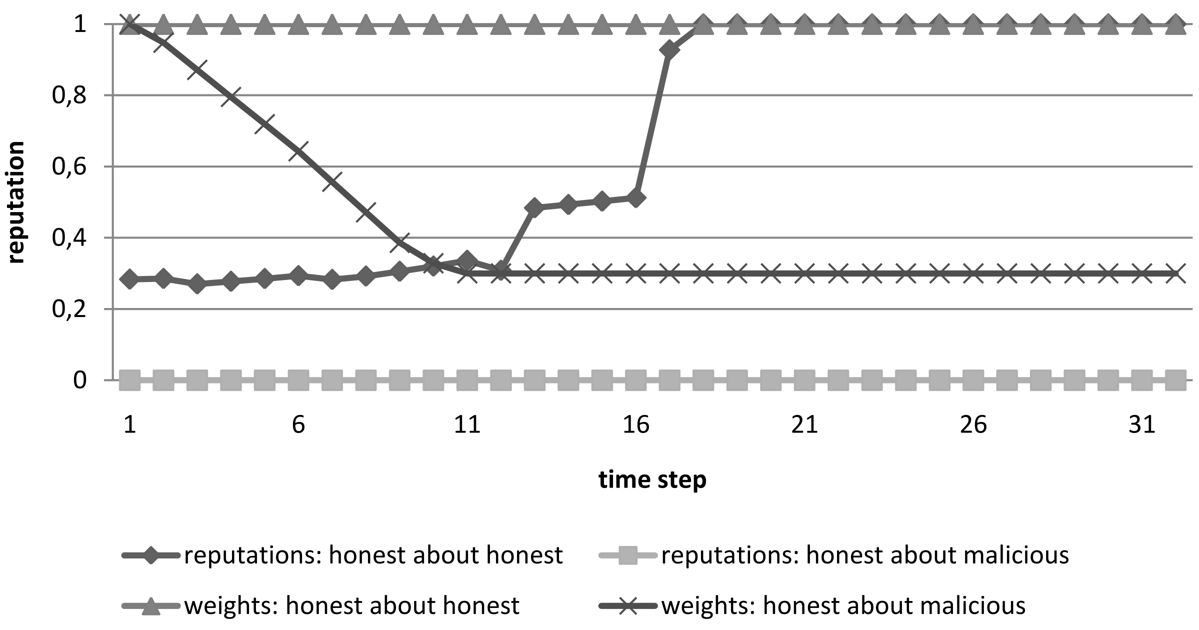


Figure 3.11.: Reputation in a network with 50% malicious nodes and threshold 0.5

with some malicious nodes, therefore no results are returned from reputation requests from these nodes. This is especially true, since the evaluation used the TEM middleware that handles reputation requests internally based on the saved data of the services. Services can only save the results of their experiences into the middleware. If no results were saved, the middleware does not return any value, thus preventing a malicious service to, e.g, return 0 to every reputation request. By not receiving any reputation data from some malicious nodes no more comparisons to its own experiences can be observed, hence the weight value stays above 0. Therefore the average weight stays above 0.

Figure 3.12 shows an interesting effect of a single isolated node in a network with 50% malicious nodes. By chance all honest nodes interacted with a single node, in this case *node7*. This resulted in no experiences gathered with the isolated node shown in Figure 3.12. Therefore the reputation data about the honest node stayed at the starting threshold, in this case 0. The weight of the malicious nodes about the isolated node is dropping, since the malicious nodes actually did interact with the isolated node. But compared to the honest nodes, they always save a bad experience into the middleware, although the isolated node returns positive results. The comparison between the two values and the calculation of the weight is done within the middleware, which leads to the decrease of the weight. Therefore using the TEM middleware increases the robustness against malicious services. The weight stabilizes at a value > 0 due to similar results as with Figure 3.11.

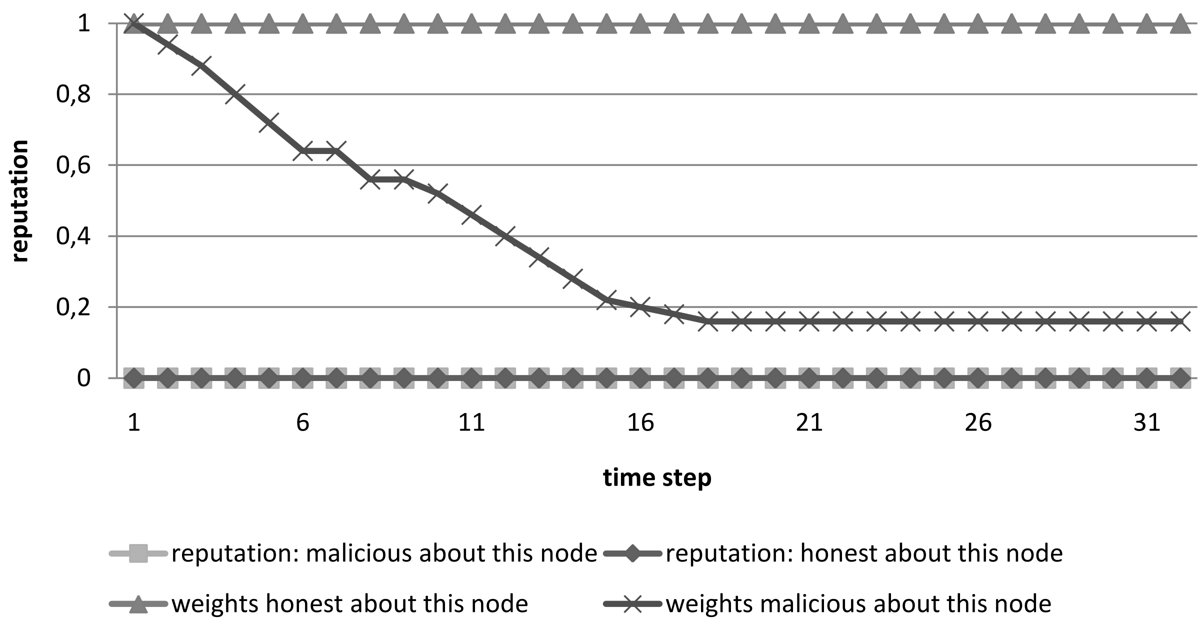


Figure 3.12.: an isolated node with 50% malicious nodes

3.3. Confidence

Direct trust itself already gives a good estimation of the observable behavior of a communication partner. But this estimation might not be very reliable itself, e.g., only a few values might not be enough to gauge the true behavior of an interaction partner, as can be seen in the evaluation of the Delayed-Ack algorithm. Therefore an estimation of the reliability of the trust value, the *confidence*, is introduced [32]. This work was done in cooperation with Gerrit Anders and Florian Siefert, University of Augsburg. The confidence consists of three parts:

1. The number of experiences c_n: A low number of experiences might not be enough to gauge the behavior correctly, as can be seen in the Delayed-Ack evaluation.
2. The age of experiences c_a: Older entries might not reflect the true behavior of an interaction partner anymore, especially when the behavior can change.
3. The variance of the experiences c_v: A high variance in the observed behavior indicates a higher uncertainty for future interactions, especially a rise in the variance might stand for a change in the behavior of the interaction partner.

The metric of every part is based on the same function, depicted in Figure 3.13:

$$f(z) = \begin{cases} 4\left(\frac{z-z_0}{z_1-z_0}\right)^3 & \text{if } z_0 \leq z \leq z_0 + \frac{1}{2}(z_1 - z_0) \\ 4\left(\frac{z-z_1}{z_1-z_0}\right)^3 + 1 & \text{if } z_0 + \frac{1}{2}(z_1 - z_0) < z \leq z_1 \end{cases}$$

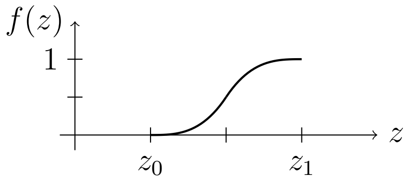


Figure 3.13.: Illustration of $f(z)$.

The characteristics of the function is based on the observations from the Delayed-Ack evaluation. Within the thresholds z_0 and z_1 only slight changes occur near z_0 and z_1, while the function changes to a a near linear characteristic in the middle. Also the function takes the value 0.5 exactly in the middle, i.e., at $\frac{1}{2}(z1 - z_0)$.

3.3.1. Number of Experiences

For the number of experiences a threshold τ_n defines, when enough experiences are gathered to set a credibility of 1. A confidence of 0 is set for 0 experiences. A trust value based on 0 experiences would be an initial trust value for instance. For our base function, this will set $z_0 = 0$ and $z_1 = \tau_n$. Based on the evaluation for Delayed-Ack a value of 25-50 for τ_n seems like an appropriate value. The formula to calculate the confidence about the number of experiences $c_n(X)$ is as follows:

$$c_n(|X|) = \begin{cases} 4\left(\frac{|X|}{\tau_n}\right)^3 & \text{if } 0 \leq |X| \leq \frac{1}{2}\tau_n \\ 4\left(\frac{|X|-\tau_n}{\tau_n}\right)^3 + 1 & \text{if } \frac{1}{2}\tau_n < |X| \leq \tau_n \\ 1 & \text{if } \tau_n < |X| \end{cases}$$

Figure 3.14 depicts the metric in a graphical way.

The function is based on the base function $f(z)$ depicted in Figure 3.13. First the function rises from 0 to $\frac{1}{2}$ at $\frac{1}{2}\tau_n$, where its gradient reaches its maximum. After that it rises with decreasing gradient to 1 at τ_n, where it stays at 1 for all values $> \tau_n$. This reflects the characteristic observed by the Delayed-Ack evaluation, see Figure 3.3, where at first the trust value was adjusting to the real trust value with a high gradient and

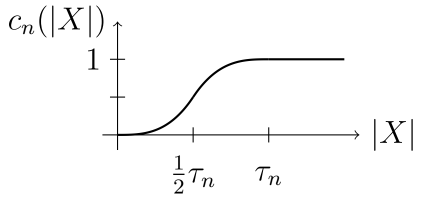


Figure 3.14.: Illustration of $c_n(|X|)$.

stabilized with decreasing gradient at the actual trust value. Similarly a small change near the edges (0 or τ_n) changes the confidence only a bit, while in the middle at $\frac{1}{2}\tau_n$ a change in the number of experiences has the highest influence on the confidence. The other parts of the confidence use functions with a similar characteristic.

3.3.2. Age of Experiences

For the age of experiences, two thresholds are introduced: $z_0 = \tau_r$ on the one hand defines the time frame, up until experiences count as up to date, therefore resulting into a confidence value of 1. $z_1 = \tau_o$ on the other hand denotes the point in time, from when experiences are considered as completely out of date, resulting in a confidence value of 0. In between those two thresholds the confidence level drops according to the basic confidence function. In total the formula for the confidence for the age of experiences is as follows:

$$r(a_x) = \begin{cases} 1 & \text{if } 0 \leq a_x < \tau_r \\ -4\left(\frac{a-\tau_r}{\tau_o-\tau_r}\right)^3 + 1 & \text{if } \tau_r \leq a_x \leq \tau_r + \frac{1}{2}(\tau_o - \tau_r) \\ -4\left(\frac{a-\tau_o}{\tau_o-\tau_r}\right)^3 & \text{if } \tau_r + \frac{1}{2}(\tau_o - \tau_r) < a_x \leq \tau_o \\ 0 & \text{if } \tau_o < a_x \end{cases}$$

Figure 3.15 depicts the formula in a graphical way.

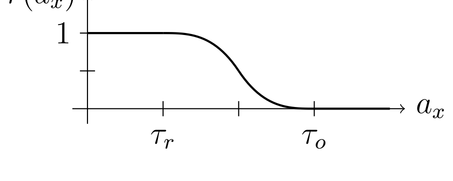


Figure 3.15.: Illustration of $r(a)$.

This formula will rate every single experience by its age. The confidence is 1 until the first threshold τ_r is reached, which marks the point, when the experience starts to get old. After that the confidence falls with increasing gradient to $\frac{1}{2}$ at $\frac{1}{2}(\tau_o - \tau_r)$. Then it falls with reducing gradient to 0 at τ_o, where it stays at for all ratings $> \tau_o$ indicating that the experience is fully outdated.

After every experience was rated, the total confidence is calculated by calculating the mean from the single confidence values:

$$c_a(X) = \frac{\sum_{x \in X} r(a_x)}{|X|}$$

3.3.3. Variance of Experiences

The variance can be used as an indication for a behavioral change, especially if the age of experiences can not be used, e.g., a change occurs during consecutive interactions. An increase in the variance, and therefore a drop in the confidence of the variance, indicates such a behavior change, since returning results will differ from the results up to this point. After some time the confidence will stabilize again. At this point the new trust value has adjusted and represents the new behavior. The formula to calculate the variance confidence $C_v(X)$ is as follows:

$$c_v(v_X) = \begin{cases} -4\left(\frac{v_X}{\nu}\right)^3 + 1 & \text{if } 0 \leq v_X \leq \frac{1}{2}\nu \\ -4\left(\frac{v_X - \nu}{\nu}\right)^3 & \text{if } \frac{1}{2}\nu < v_X \leq \nu \end{cases}$$

where v describes the highest possible variance, when the confidence reaches 0. In this case v = 0.25, which is the maximal confidence for a mean value of 0.5. For the proof for this claim see appendix A. Figure 3.16 depicts the formula in a graphical way.

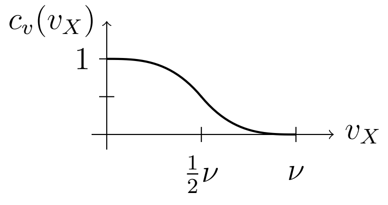


Figure 3.16.: Illustration of $c_v(X)$.

A confidence of 1 equals 0 variance, i.e., all results are identical, while a confidence of 0 marks maximal variance. The maximal confidence is dependent on the mean value, e.g., the maximal confidence for a mean value of 0.5 is 0.25 whereas the maximal confidence for a mean value of 0.4 is 0.24. Because v of the confidence formula is chosen statically to be 0.25, only a distribution around the mean value 0.5 can actually reach confidence 0, all others will have a minimum confidence greater than 0. The closer the mean value is to 0 or 1, the closer is also the minimum confidence for the variance. If v is not chosen to be 0.25, but to be the maximum variance for the according mean value (the trust value here) unintentional effects can be observed. A variance of 0.1 would translate to another confidence value for a maximal variance of 0.25 than for a maximal variance of 0.24 since the function characteristics are slightly compressed. One would expect the same confidence value of identical variance values. Instead the total maximum of 0.25 is always chosen as v and the minimum confidence is instead changed, the function is cut off at the lower end.

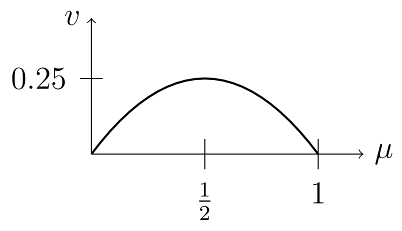


Figure 3.17.: maximal variance v

Figure 3.17 demonstrates the behavior of the maximal variance v compared to mean values μ. The maximum is, as mentioned above, at $v = 0.25$ for $\mu = 0.5$. The characteristics are similar to the other two functions. The confidence is 1 for a variance of 0 and falls with increasing gradient to $\frac{1}{2}$ at $\frac{1}{2}v$. After that it drops with a decreasing gradient to 0 at v. Since the variance is between 0 and v, the maximal variance, this marks also the domain of the variance confidence.

All three parts of the confidence metric are aggregated to a total confidence value c with configurable weights:

$$c = \frac{w_n c_n(|X|) + w_a c_a(X) + w_v c_v(v_X)}{w_n + w_a + w_v}$$

where w_n is the weight for the number of experiences, w_a the weight for the age of experiences and w_v the weight for the variance of experiences. Each application is able to adjust the weights according to their requirements. By default all parts are weighted equally, i.e., $w_n = w_a = w_v = 1$.

3.3.4. Evaluation

To evaluate the effectiveness of the confidence metrics, a network consisting of 100 agents was created. Another dedicated agent chooses in every timestep, with which of the 100 possible agents it wants to interact with. Each agent i has a mean benefit b_i. The 100 agents were created using 4 different types:

- Type 1: $b_i \in [0.85, 0.95]$ (30 agents)
- Type 2: $b_i \in [0.55, 0.65]$ (40 agents)
- Type 3: $b_i \in [0.4, 0.5]$ (20 agents)
- Type 4: $b_i \in [0.2, 0.3]$ (10 agents)

In addition, the agents have a variance of v_i in their behavior. The agents of each type have $v_i = 0.1$ (40%), $v_i = 0.05$ (30%) and $v_i = 0.025$ (40%). The benefit of an interaction with such an agent is created by using a beta distribution with their mean b_i and variance v_i. In addition a sliding time window was used, only taken into account the last 30 interactions to calculate the trust value and the corresponding confidence values.

As a first evaluation the dedicated agent interacted 100 times in a row with a single agent i with the following characteristics:

- The Agent i was of Type 2 with $b_i \approx 0.6$ and $v_i = 0.1$.
- Agent i changed its behavior to Type 4 with $b_i \approx 0.2$ and $v_i = 0.1$ after 60 timesteps.
- The confidence formulas were parametrized with $\tau_r = 30$, $\tau_o = 40$ and $\tau_n = 25$.

The interaction with this agent is conducted in 3 steps:

1. An interaction per timestep for 30 timesteps.
2. Type change from Type 2 to 4 at timestep 30, but no further interactions for another 30 timesteps.
3. Again one interaction per timestep for 40 timesteps, up to a total of 100 timesteps.

Figure 3.18 displays the evaluation and the three steps.

In part 1, up until timestep 30, the dedicated agent interacts once per timestep with agent i. The trust value evens out on the mean benefit b_i of the agent i. The confidence of the number of experiences (c_n) increases up to its threshold τ_n, where it stays at 1. This covers the time the trust value needs to even out and correctly represents the mean benefit this agent facilitates. Since there are experiences in every timestep, the confidence about the age of experiences stays at 1. The confidence of the variance stabilizes at around 0.75. This value is below 1, because the benefit of the agent varies

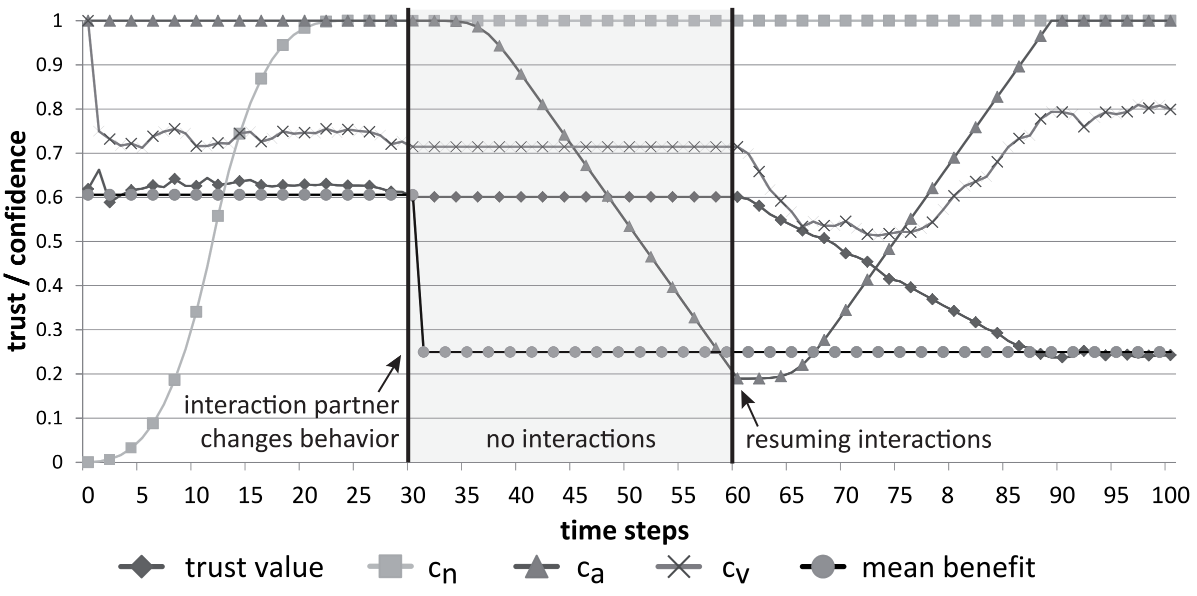


Figure 3.18.: Confidence values of a single agent

per transaction, as can be seen in the value v_i.

In part 2, after the behavior change and interactions stop, the trust stays at its old value, since no more interaction indicate its change. However, the experience age and the corresponding confidence value drops. At timestep 60, 20 out of the 30 gathered experiences have fully expired and therefore have a confidence rating of 0 regarding their age. The 10 newest, which are still 30-40 timesteps old, have decreasing values of confidence. In total this brings the confidence down to about 0.2. The variance confidence is stable, since only the data from timestep 1-30 are still available and they do not change after the additional 30 timesteps have passed.

In part 3, interactions with the agent i are resumed and continued for another 40 timesteps with one interaction per timestep. With interactions that return values according to the new benefit gain, the trust value drops until it reaches the expected value, where it stabilizes. Since new interactions are conducted the age confidence increases until it reaches 1 again. The interesting part is the variance confidence. Since the new interaction results now differ from the old values the variance increases and therefore the corresponding confidence drops. After more of the new interaction results are gathered, the system adapts to the new behavior and as the trust value reaches its real value the variance confidence stabilizes at its new value, indicating the trust value is accurate again.

After initially investigating the different parts of the confidence metric, the designated agent now chooses 1 agent out of all 100 in every timestep to interact with. The selection metrics are based on a roulette-wheel metric. A roulette-wheel metric assigns all choices a possibility value and chooses randomly, where choices with a higher value have a higher chance to be selected. In total 4 selection metrics were used:

- *selRdm*: An agent was chosen randomly using a uniform distribution, setting a baseline for comparison.
- *selTrust*: The designated agent calculated the trust values for all agents and selected an interaction partner by a roulette-wheel selection method.
- *selTrustConf*: The designated agent additionally assessed its confidence in these trust values and used the product of trust and confidence in combination with a roulette-wheel selection method.
- *selTrust^{2}Conf*: This method determined an interaction partner in two stages. First, a set of 10 agents was selected by using the selTrust method. Subsequently, the designated agent selected its interaction partner by using the selTrustConf selection method.

The evaluation goes for 8000 timesteps with 2 behavior changes at timestep 2000 and 4000:

- Type 1: 6/4/2 agents changed to Type 2/3/4[1].
- Type 2: 6/6/2 agents changed to Type 1/3/4.
- Type 3: 4/6/1 agents changed to Type 1/2/4.
- Type 4: 2/2/1 agents changed to Type 1/2/3.

All agents are initiated with a trust value by conducting exactly 1 interaction, before the evaluation itself is started. Due to the higher amount of possible interaction partners, a long time span might occur between 2 interactions with a single agent, therefore the age confidence metric got parametrized differently, i.e., with $\tau_r = 2000$ and $\tau_o = 3000$. The total confidence was calculated with $w_n = w_a = w_v = \frac{1}{3}$, giving all 3 parts equal weight for the total confidence value. The results are averaged from 200 evaluation runs.

Figure 3.19 displays the average gain in benefit of the designated agent of the last 50 interactions per time step. The random selection metric *selRdm* has the lowest gain of benefit but is stable throughout the evaluation. Using trust alone (*selTrust*) already increases the gain in benefit by approximately 9.54% compared to *selRdm* at time step 8000. At timestep 2000 and 6000, when the behavior chances, a drop in the gain of benefit can be observed. This is to be expected, since agents with former good benefit are chosen although they now act a lot worse. The system acknowledges this change though and stabilizes again. Regardless, *selTrust* never drops below *selRdm*, even shorty after the changes. Adding confidence to trust with the simple method of *selTrustConf* increases

[1]Type 1: 6/4/2 agents changed to Type 2/3/4 means: 6 agents of type 1 changed to type 2, 4 agents of type 1 changed to type 3 and 2 agents of type 1 changed to type 4.

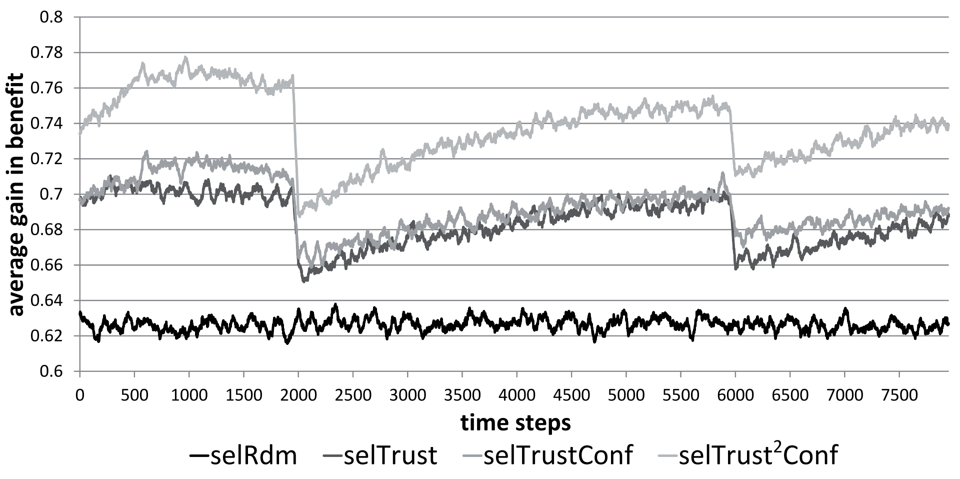


Figure 3.19.: Average gain in benefit

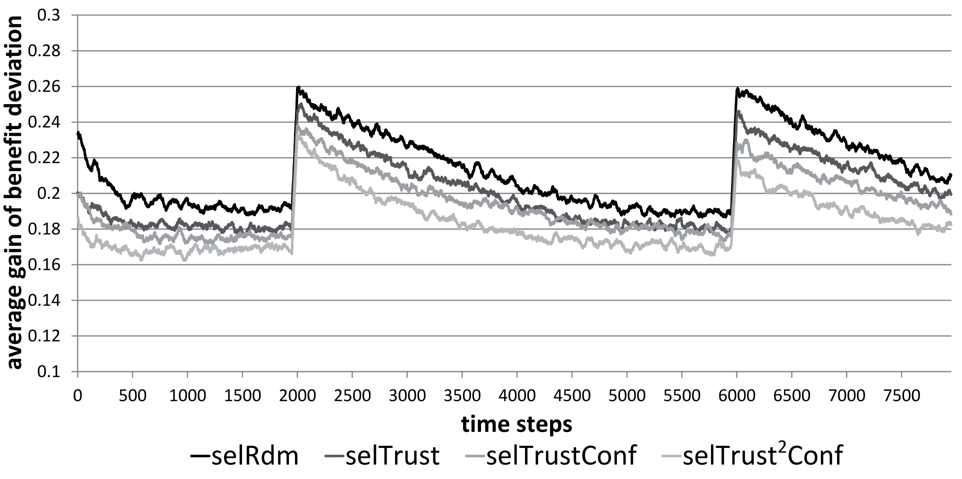


Figure 3.20.: Average difference between expected and real gain in benefit

the benefit gain, but not significantly, whereas the more complex metric *selTrust*^{2}*Conf* does strongly increase the benefit gain, by 17.84% compared to *selRdm*.

Figure 3.20 displays a slightly different sight on the evaluation. Here the difference between the expected benefit and actual benefit is depicted. The lower the difference, the better. *selRmd* is displayed here as comparison, but the data was not used for selection purposes. Similar to the benefit gain, *selRdm* is the worst metric and *selTrust*^{2}*Conf* the best.

3.4. Aggregating Direct Trust and Reputation

With the confidence defined, direct trust t_{dt} and reputation t_r can now be aggregated to a total trust value:

$$t_{total} = w_c \cdot t_{dt} + (1 - w_c) \cdot t_r$$

The weight w_c is calculated using the confidence. The higher the confidence, the higher w_c and therefore the higher the influence direct trust has over reputation. The function to calculate the weight from the confidence is depicted in Figure 3.21. It is based on the same function as the confidence metrics, see Figure 3.13.

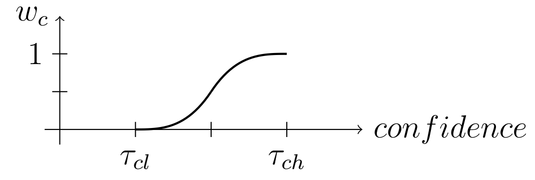


Figure 3.21.: Illustration of $f(confidence) = w_c$.

Mathematically the function is defined as

$$w_c = \begin{cases} 0 & \text{if } c < \tau_{cl} \\ 4\left(\frac{c-\tau_{cl}}{\tau_{ch}-\tau_{cl}}\right)^3 & \text{if } \tau_{cl} \leq c \leq \tau_{cl} + \frac{1}{2}(\tau_{ch} - \tau_{cl}) \\ 4\left(\frac{c-\tau_{ch}}{\tau_{ch}-\tau_{cl}}\right)^3 + 1 & \text{if } \tau_{cl} + \frac{1}{2}(\tau_{ch} - \tau_{cl}) < c \leq \tau_{ch} \\ 1 & \text{if } \tau_{ch} < c \end{cases}$$

There are two thresholds defined:

- τ_{cl} marks the threshold for too low confidence. When the confidence is lower than τ_{cl} the weight w_c is set to 0, resulting in using only reputation for the aggregated value.
- τ_{ch} marks the threshold for high confidence. When the confidence is higher than τ_{ch} the weight w_c is set to 1, resulting in using only direct trust and no reputation for the aggregated value.

Having all trust parts combined, two questions arise:

1. What are appropriate values for τ_{cl} and τ_{cr}? These two thresholds define the area, when to switch from reputation to direct trust. For humans this point is highly

subjective and therefore a quantification of it proves difficult.

2. How do the parameters of the different metrics influence the result and which parts (direct trust, reputation, confidence and aggregation) of the metrics are favorable for future decisions.

The metrics for confidence, reputation, and aggregation define a total of 12 different parameters. The direct trust metric itself is not parametrized, since it is either application specific (when rating application interaction) or surveyed by the Delayed-Ack algorithm for node reliability, which is not parametrizable. Table 3.1 summarizes the different parameters defined in the trust metrics.

Table 3.1.: Parameters to configure the metrics direct trust with confidence (DTC, top only) and direct trust with confidence and reputation (DTCR, top and bottom part); also the history length needs to be defined for all metrics.

w_n	$\{0, 1, \ldots 10000\}$	weight for the number confidence
w_a	$\{0, 1, \ldots 10000\}$	weight for the age confidence
w_v	$\{0, 1, \ldots 10000\}$	weight for the variance confidence
τ_n	$\{0, 1, \ldots 50\}$	threshold for the number confidence
τ_r	$\{0, 1, \ldots 8000\}$	recent experiences threshold for the age confidence
τ_o	$\{0, 1, \ldots 8000\}$	outdated experiences threshold for the age confidence
r_s	$\{0.1, 0.2, \ldots 1\}$	initial weight for the reputation
θ	$\{0.00, 0.01, \ldots 1\}$	maximal weight adjustment per experience for the reputation
τ	$\{0.01, 0.02, \ldots 1\}$	threshold for positive weight adjustment for the reputation
τ^*	$\{0.01, 0.02, \ldots 1\}$	threshold for the negative weight adjustment for the reputation
τ_{ch}	$\{0.00, 0.01, \ldots 1\}$	high confidence threshold for the aggregation weight
τ_{cl}	$\{0.00, 0.01, \ldots 1\}$	low confidence threshold for the aggregation weight

All these parameters span a total design space of $\approx 3.36 * 10^{32}$ possible configurations. A complete investigation of such a large design space is not feasible, therefore an *Automated Design Space Exploration (ADSE)* utilizing heuristic search algorithms, e.g., particle swarm optimization or genetic algorithms, is performed. A definition of ADSE and the algorithms used are presented in Chapter 4, which contains the scenario to evaluate these metrics. Through ADSE the other research question to identify appropriate values for τ_{cl} τ_{cr} is also feasible. First results of the evaluation were published in [34]. Chapter 4 presents the basis scenario but expands it with further evaluations.

4. Evaluating the Effects of all Trust Metric Parts

This chapter describes the scenarios to evaluate the aggregation metric, i.e., the combination of direct trust and reputation using the confidence to calculate the weight between the two. It is similar to the scenario for the confidence, with the following enhancements:

- The parameter space of the different metrics is traversed by an Automated Design Space Exploration to identify the best parameters as well as the influence these parameters have on each other.
- Besides direct trust and direct trust with confidence, the aggregation of direct trust and reputation with the help of the confidence is evaluated and compared to the other two metrics as well as random.

In addition, the difference between trust calculations based on continuous and binary experience ratings is investigated. On the one hand the Delayed-Ack algorithm for reliability rates message transitions either with 0 (*not received*) or 1 (*received*). On the other hand the algorithms for credibility applied by the other research groups of the OC-Trust project rate their experiences with continuous values [3][2]. Furthermore the influence of behavior changes, especially the amount of their occurrences, for both experience ratings (binary and continuous) are examined.

Section 4.1 describes the automated design space exploration (ADSE) used to investigate the effects, that different amounts of behavior changes and different kinds of experience ratings might have. Section 4.2 presents the evaluation environment, in which all evaluations are conducted. Then the results for different behavior change amounts are presented, each for continuous and dual experience ratings. The fist scenario, described in Section 4.3 features 8 behavior changes that increase in occurrence before the system stabilizes again. In a second scenario, described in Section 4.4, only 2 behavior changes, far apart, are examined. Finally, in Section 4.5, a volatile system with 160 behavior changes is examined.

4.1. Automated Design Space Exploration

The general idea of an *Automatic Design Space Exploration* (ADSE) is to find good values for parameters with heuristic (e.g. genetic) algorithms automatically; this is especially useful when a mathematical solution is not easy to reach. The core algorithm defines values for all parameters; such a set of values is called *configuration* and represents a point in the multi-dimensional *design space* or *parameter space*. The quality of a configuration is measured by a single or multiple performance indicators called *objectives*. Typically, there are a lot more parameters than objectives.

Alternative methods to find good configurations are *manual exploration* and *exhaustive search*. In a manual exploration an engineer manually tries to find good configurations ("educated search"). Although this method can provide results very quickly there is a high risk of stopping in a local optimum, hence the best global solution is not found. In an exhaustive search all possible configurations are evaluated. Hence it is guaranteed to find the global optimum. Nevertheless, the price for evaluating all possible configurations is high; for large design spaces this method is simply not applicable.

An ADSE, especially if run with widely accepted good quality algorithms, can both dramatically reduce the number of necessary evaluations and reduce the risk of finding local optima as well.

The dominance relationship defines an order for configurations. A configuration i dominates another configuration j if all values of the objectives for i are better or the same and for at least one definitely better than those of j. The true Pareto front is defined as the optimal set consisting of all non-dominated individuals. It is approximated during the ADSE by the set of known non-dominated individuals, which is called approximated Pareto front.

Different exploration runs can be compared with the hypervolume, also called hyperarea. It is the region between the so-called hypervolume reference point and the approximation of the Pareto front. The higher the hypervolume is, the better is the found approximation of the Pareto front.

The *Framework for Automatic Design Space Exploration (FADSE)* provides a way to reduce development effort for fast and reliable explorations with standard algorithms. It was originally presented by Horia Calborean to find optimal configurations of processor architectures [9][10] and was later enhanced for robustness and to accelerate explorations by parallel evaluations [8]. It is now able to optimize both hardware and code optimization parameters [27], e.g., FADSE is implemented completely in Java and available as open source[1].

[1]Homepage of FADSE: `http://code.google.com/p/fadse/`

The main advantages of FADSE are that it provides (a) best-practice standard algorithms, which are modified for (b) parallel evaluation of the individuals of a generation and (c) accelerated with a database to avoid re-evaluation of an already known individual. Also, FADSE features (d) mechanisms to improve robustness of the evaluation, i.e., it can automatically recover from errors in the evaluation of an individual, deal with infeasible individuals, and stores checkpoint files after every generation allowing a late resume of an exploration.

ADSE applies *genetic and particle swarm algorithms* to heuristically search the design space for an optimal enough solution. Commonly these algorithms do not find the global optimum, but typically find a local optimum that is quite close to the global optimum.

Genetic Algorithms [23] try to mimic evolution. Each configuration is defined as a vector and called an individual, where each element of the vector represents one parameter. A generation contains a set number of individuals, e.g., 100. Each individual of a generation is rated by a fitness function. After each individual was rated, a new generation is created by building offspring using crossover and mutation of selected individuals. Crossover takes two individuals and combines one part of the first individual's configuration with another part of the second individuals's configuration. Mutation randomly changes some part of an individual. After that some individuals of the original generation are replaced with the newly generated individuals. Then the algorithm starts again with the new generation until a defined number of generations are processed. The initial generation is created randomly. How to conduct crossover, mutation, and what individuals to replace on a new generation depends on the algorithm used. In this work the NSGAII [13] genetic algorithm was used for FADSE.

Particle Swarm Algorithms [46] take natural swarms, like fish schools or swarm of birds, as basis. A number of individuals are randomly created. Similar to genetic algorithms, each individual represents a configuration. Each individual (consisting of n different parameters) moves through the design space with an n-dimensional velocity vector. This vector is composed of three components: (1) its old velocity vector, (2) the difference between its current and its best known position and (3) the difference between its current position and the best known position of the entire swarm. These three parts are weighted to create the final velocity vector and can be parametrized, e.g., a high weight for (1) would focus on exploring the design space. In addition (2) and (3) include random modifiers to add some individualism to each particle. In this work the particle swarm algorithm SMPSO [45] was used for the evaluation.

Since the particle swarm algorithm SMPSO provided better results than NSGAII all evaluations were conducted using SMPSO instead of NSGAII.

4.2. Abstract Evaluation Scenario

The evaluation is based on agents of a Multi-Agent System (MAS), which want to interact with each other to further their personal goals. The MAS consists of 10 evaluation agents that decide each time step with which of 100 possible agents to interact with. These agents reply to an interaction request with either a continuous value between 0 and 1 (first evaluation type) or with a binary value of 0 or 1 (second evaluation type). These replies represent the quality of the interaction, with 0 being the worst and 1 being the best possible outcome. This result is the *benefit* an agent gets from this interaction and is a quality measure for the selection of the transaction partner. The agent can either be a service, which rates the credibility of another service or a node, which rates the reliability of another node.

In a real life system the entity that initiated the interaction needs a way to evaluate the quality of an interaction to be able to rate it. The Delayed-Ack algorithm rates interactions with either 0 or 1, 1 being a received message, 0 for a message that was lost. The credibility algorithms of the other OC-Trust groups rate their experiences with values between 0 and 1. Both cases are evaluated for each scenario). In the simulation, we assume each agent performs predictably. This means that, on average, an interaction with an agent leads to the same result, although with some variation. This is archived by using a beta distribution [29] with a specific mean value μ and a variance. A beta distribution additionally provides the possibility to simulate other distribution functions to simulate alternative behavior, e.g. mean distribution with $\alpha = 1$ and $\beta = 1$ to simulate completely random behavior. For binary experience values, a random number (r) from the beta distribution is rounded to either 0 ($\mu < r$) or 1 ($\mu \geq r$).

An exemplary agent could be one for face recognition. Based on the hardware it is running on and the quality of the algorithm, its results should be on the same level of quality. Nevertheless there can be variations depending on the quality of the picture it has to work with.

To simulate different agent qualities, four types of agents are defined with different mean values μ for the benefit that can be gained from interacting with one of them:

- Type 1: $\mu \in [0.85, 0.95]$, 30 agents
- Type 2: $\mu \in [0.55, 0.65]$, 40 agents
- Type 3: $\mu \in [0.4, 0.5]$, 20 agents
- Type 4: $\mu \in [0.2, 0.3]$, 10 agents

Additionally, the agents of each type are initialized with different variances σ^2 for their mean benefits:

- high variance of $\sigma^2 = 0.15$, 40% of agents within each type group
- medium variance of $\sigma^2 = 0.1$, 30% of agents within each type group
- low variance of $\sigma^2 = 0.05$, 30% of agents within each type group

Over time, the agents can change their behavior. In real life, this could, e.g., be triggered by environment factors like a reduction of available computing capacity by a user, which would increase response time of an agent and therefore the quality of the outcome. To model the switches in agents' behaviors the following changes are performed[2]:

- Type 1: 6/4/2 agents change to type 2/3/4.
- Type 2: 6/6/2 agents change to type 1/3/4.
- Type 3: 4/6/1 agents change to type 1/2/4.
- Type 4: 2/2/1 agents change to type 1/2/3.

An evaluation is performed for 8000 time steps, where each evaluation agent chooses one agent to interact with and performs a single interaction. In total, 50 such evaluations were per scenario and averaged. Only the results of the first evaluation agent are observed to ease comparability and because the other nine of ten evaluation agents are needed only for their reputation values. In case of direct trust as selection metric, calculating the average result of all ten agents would influence the overall result negatively because a kind of reputation would also be considered.

Each time step the evaluation agents have to decide, with whom of the 100 agents to interact with. The metric used for that decision is called the *selection metric*. In total, four selection metrics are used.

All metrics beside the random metric are based on roulette wheel selection, similar to the evaluation of the confidence metric, see Section 3.3. For this, all possible candidates are placed on a metaphoric roulette wheel, whereas a higher factor for a candidate means a bigger fraction of the wheel. Then a random number is taken to choose the candidate. A candidate with a higher trust value has a higher chance to be picked than someone with a lower trust value. By using this base metric we give the evaluation agents the chance to still explore possible other agents to interact with while still having a high chance to exploit already known good agents.

- **Random (RAND):** A random selection metric is used as baseline. This metric picks one of the 100 agents randomly in each time step.
- **Direct trust (DT):** In this selection metric, only direct trust is used as selection metric. Trust is calculated by a normal mean metric. The trust values are used

[2] *Type 1: 6/4/2 to type 2/3/4* means that 6 agents of type 1 switch their behavior to type 2, 4 of type 1 switch to type 3, and 2 of type 1 switch to type 4, and vice versa.

for the roulette wheel metric.

- **Direct trust and confidence (DTC):** In this metric we add confidence as selection parameter. For that we use a two step approach, similar to the confidence evaluation:
  1. Calculate the direct trust values for all agents and choose 10 different agents by using the roulette wheel metric.
  2. Calculate confidence for these 10 agents, multiply it with trust value and use the result for a second round of roulette wheel.

  Such a two step approach always yields better results than executing step 2 alone. This effect can be seen in [32].
- **Direct trust, confidence, and reputation (DTCR):** In this metric reputation is additionally considered. The metric is similar to trust and confidence, as that a two step roulette wheel metric is used again. Step 1 is identical as before, whereas step 2 uses the trust aggregation metric described in Section 3.4. As reputation data, the direct trust data of the other nine evaluation agents are taken.

4.3. Scenario with Some Behavior Changes

In the first scenario, a total of 8 behavior changes are conducted. They are triggered after 1000 time steps and again after 1000, 200, 500, 200, 100, 2000, and 2000 time steps. The last 1000 time steps do not have any more behavior changes. This mimics a system, that is stable for a time, then starts to fluctuate in its behavior until it stabilizes again. Evaluations with continuous as well as binary experience values are run to investigate the influence and difference of these two different ratings.

4.3.1. Continuous Experience Ratings

In this section, experiences are rated with continuous values, i.e., values between 0 and 1. The following results show the total cumulative benefit compared to the history length for every selection metric. The points displayed in the graphs are all configurations evaluated by SMPSO in all exploration runs. Because of the optimization goals the number of generated and evaluated configurations is more dense in the top-left corner and not equally distributed.

Selection metric **random (RAND)** with benefit 5018 is taken as baseline.

The selection metric **direct trust (DT)**, see Figure 4.1, is not influenced by parameters besides the history length. Hence its results do not show any variance. It can be seen that with lower history length better results are achieved, whereas using only the most recent experience (history length is 1) results in the worst observed benefit. A history length of 2 is the most profitable setting in the evaluated scenario. Only a few experiences as history give the system the chance to adapt quickly to changes. In comparison, if the history length is a high value, then the history can also contain many already out-dated experiences. They do not reflect the current behavior of the agent anymore, and hence have a negative impact on the trust value. When the agent is not changing its behavior, i.e., is in a stable state, the last few experiences are enough to model its upcoming behavior accurately, too.

Figure 4.2 depicts the results for selection metric **direct trust and confidence (DTC)**. The resulting benefit is higher compared to direct trust (DT) only but features a high variance; especially with low history length very low benefits can be observed. The trend of a higher benefit with lower history length is still visible. The top values are at history length 2-3. While giving generally better results than with only direct trust (DT), the high variance of the results shows that adding confidence might result in worse benefit compared to only direct trust (DT) if the parameters are set unwisely.

The results for selection metric **direct trust**, **confidence**, and **reputation (DTCR)** are displayed in Figure 4.3. By adding reputation, the best results for every history length are comparable to the results of selection metric DTC. The trend of lower history length leading to better benefits is unchanged. The important difference to metric DTC is the variance of the data and the benefit obtained with unluckily chosen parameter values. The variance is much smaller than without reputation. Also there are no low runaway values, which leads to much more stable results.

Concluding, the evaluation shows that with all three aspects, i.e., direct trust, confidence, and reputation, much better and more robust results can be achieved. In addition, we did not observe any configuration[3] with metric DT, DTC, or DTCR, that showed lower benefit than metric random (RAND)[4]. The impact of the history length on the benefit seems surprising because the best results were achieved not with a high number of past experiences but with only a few of them.[5] However, a low history length gives the system a chance to swiftly adapt to changing agent behavior.

The observed minimum and maximum values for all selection metrics are shown, in comparison to RAND as baseline, in Figure 4.4. The history length was set to 2. In order to get the displayed observed worst benefits, SMPSO was configured to minimize

[3]In total, about 40,000 configurations were evaluated.

[4]Nevertheless, it is not impossible but extremely unlikely that always the best theoretical agent is selected by chance and hence better results can also be achieved non-deterministically with metric random (see *infinite monkey theorem*).

[5]The dominant points are found in all three Figures for history lengths 1, 2, and 3. Because of this, a typical Pareto front cannot be observed; it consists only of these three configurations.

benefit, hence looking for the worst configuration. As mentioned before, with direct trust (DT) a higher benefit than random is archived. Adding confidence (DTC), the benefit can be increased but with the possibility of getting worse benefit if parameters are chosen unwisely. Nonetheless, the worst result for direct trust with confidence (DTC) is still better than with random (RAND). By adding reputation (DTCR), the worst found result is significantly better; it is even better than the best result of direct trust (DT) alone. Reputation seems to reduce the effects of bad parameter settings and leads to good results, even in the worst case.

Figure 4.1, 4.2, and 4.3 show that the history length is generally the dominating factor for the benefit. Figure 4.2 shows as well, that even with a history length of 2, the cumulative benefit can be quite low for selection metric DTC, if the other parameters are chosen unluckily.

To get an idea about how to set the different parameters in order to have a very good benefit with high probability the configurations were classified into two groups. The best 10% of all configurations are classified as very good and are the group that should be isolated from all the other configurations. With statistical analysis and a decision tree calculated automatically with the algorithm C4.5 [49] the following was observed:

- **Amount confidence:** The threshold of the amount confidence τ_n must not be higher than the history length, therefore there is not much choice how to configure it with such low history length values. The weight for this part of the confidence was generally set quite high in the DTC metric. In the DTCR metric the weight was set relatively uniformly over the domain range.
- **Age confidence:** In the DTC metric, the thresholds were set far apart, i.e., a lower value for τ_r and a higher value for τ_o, creating a larger gray zone. In contrast, the thresholds did not show any trend in the DTCR metric. For the weight, no trend was discernible for the DTC or the DTCR metric.
- **Variance confidence:** The weight for the variance metric tended to be at a lower value for the DTC metric, while showing no trend in the DTCR metric.
- **Reputation metric:** The τ threshold tended towards a low value, while the τ^* value spanned a higher range. This means a narrow range for the reputation weight to increase, with a wider range for it to decrease. An agent thus expected a high similarity to increase the weight and was fast to reduce the weight. The maximum adjustment θ for the reputation just showed a value of 0.8 or lower, but was uniformly distributed within that interval. The initial weight r_s was distributed over the entire domain with a slight preference in the value range of > 0.5.
- **Aggregation metric:** When looking at the thresholds for the aggregation method a strong trend to always consider reputation can be seen. Nearly all of the values

for τ_{ch} were set near confidence 1. This means that the area when taking no reputation into account was practically non existent. On the other hand, the low threshold τ_{cl} was set relatively low, which also resulted in a nearly nonexistent area for using direct trust only. In total, the transition from reputation only to direct trust only seems to be fluent.

To summarize, the history length appears to be the dominating factor. An explanation would be, that by using a low amount of experiences, the system can adjust quickly to changes, while some experiences are also enough, when the behavior of an agent is consistent over time. Another interesting result is the combination of direct trust and reputation. Both of them are important to use with a fluent transition between them. Reputation strongly helps to counteract possibly wrong decisions, which explains the missing trends for the confidence parameters: Due to the corrective ability of the reputation, the parameters for the confidence are less influential. In human society, both direct trust and reputation are applied for decision making and our evaluation has shown, that this also applies for computational agent societies.

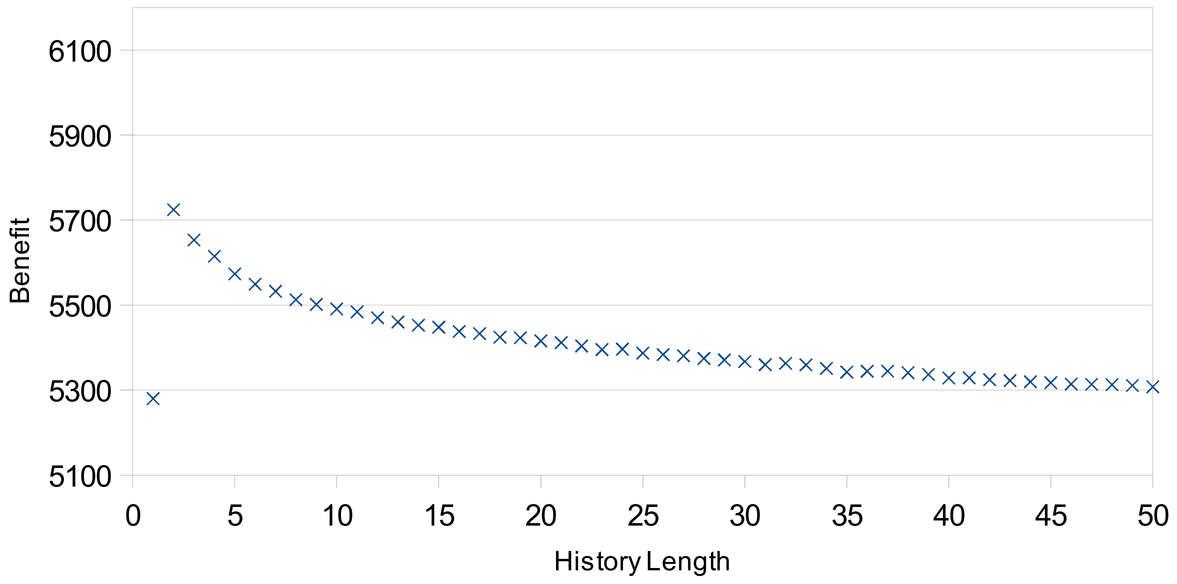


Figure 4.1.: Benefit versus history length for selection metric direct trust (DT) using continuous experience ratings (8 behavior changes)

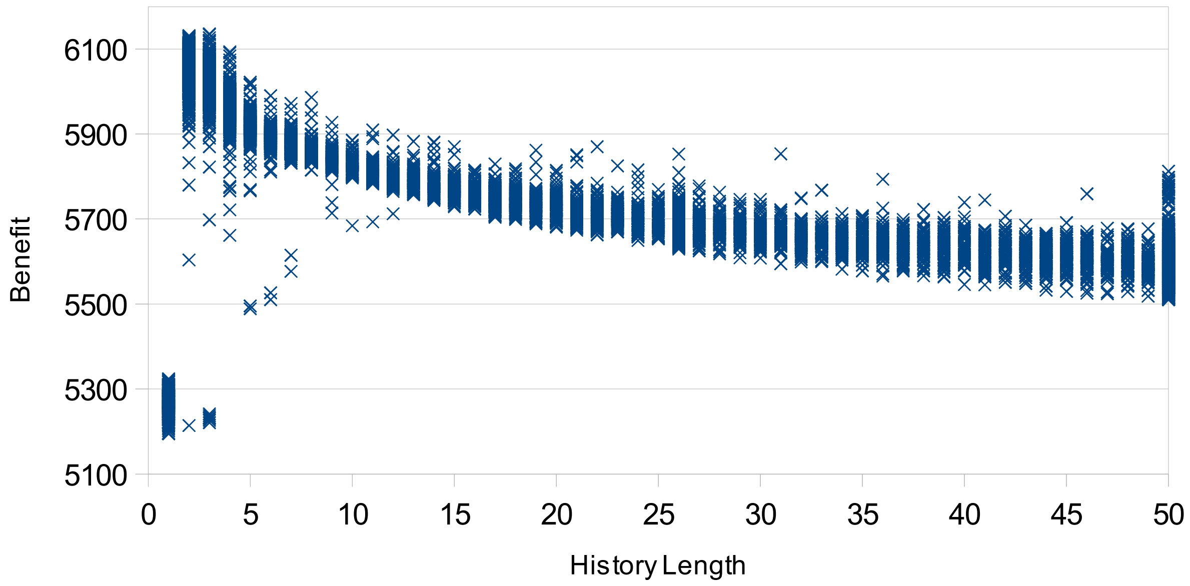


Figure 4.2.: Benefit versus history length for selection metric direct trust and confidence (DTC) using continuous experience ratings (8 behavior changes)

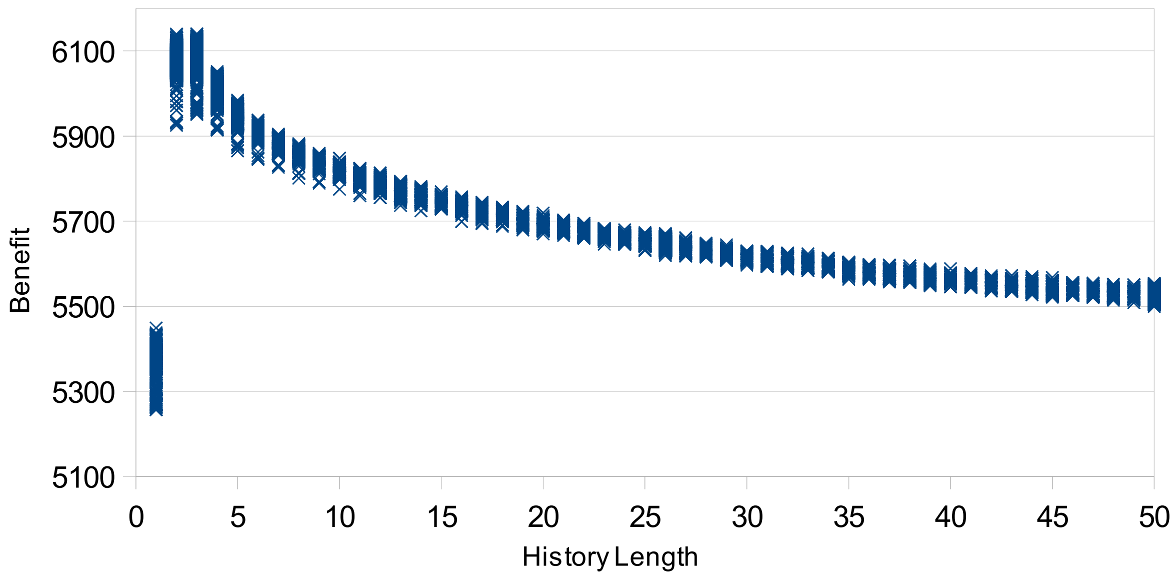


Figure 4.3.: Benefit versus history length for selection metric direct trust, confidence, and reputation (DTCR) using continuous experience ratings (8 behavior changes)

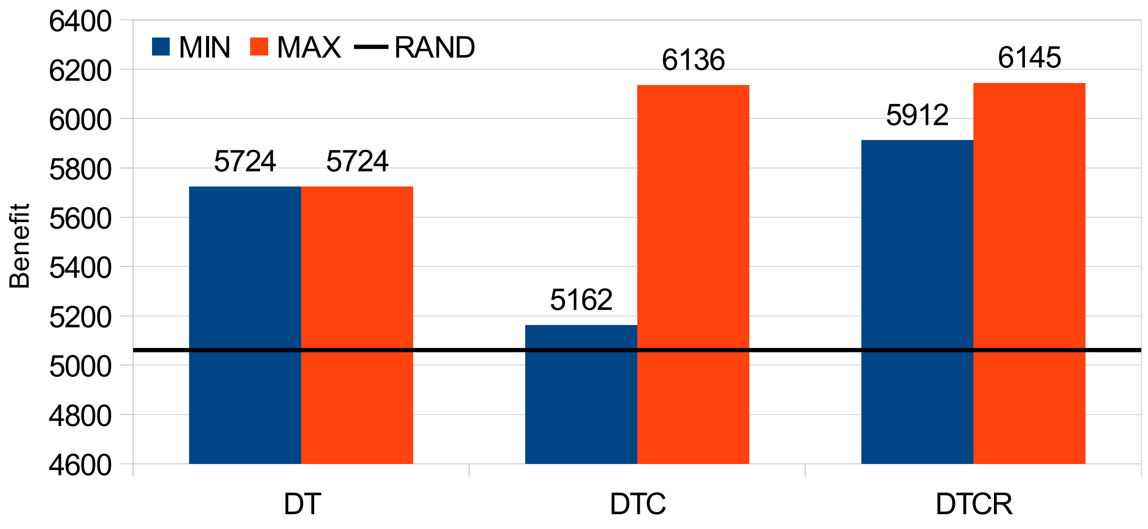


Figure 4.4.: Best and worst observed results for each selection metric in comparison with random (RAND) for history length 2 when using continuous experience ratings (8 behavior changes)

4.3.2. Binary Experience Ratings

The aforementioned evaluation was based on experience ratings between 0 and 1. Such an assumption can be made if the direct trust values are credibility values, e.g., when evaluating the amount of correctly tagged faces on a picture using a face recognition algorithm. In such a case, a single misclassified face does not result in an experience rating of 0, but a value between 0 and 1. In other cases, i.e., with the Delayed-Ack algorithm, the direct trust values can only be set to either 0 or 1.

To investigate the differences between using binary experience values and continuous ones, a similar experiment was conducted. There the agent behavior is based on a beta distribution with a target mean value and a variation. The agent configuration is the same as for the first experiment, but the continuous values from the beta distribution are rounded in the following way: If the number drawn from the beta distribution is smaller than the mean value, it is rounded down to 0. Otherwise it is rounded up to 1.

Again an automated design space exploration (ADSE) was executed to find the best configuration for the direct trust (DT), direct trust and confidence (DTC) as well as direct trust, confidence and reputation (DTCR) metrics regarding the parameters described in table 3.1.

Figure 4.5 shows the results for the **DT selection metric**. Since nearly all by ADSE investigated parameters described in Table 3.1 are for confidence, reputation and aggregation, the only free parameter is the history length. Similar to continuous experience values a lower history length is favorable to gain a high benefit.

Figure 4.6 shows the results for the **DTC selection metric**. The results show a similar trend towards lower history length for higher benefit. The vast majority of good results is observed with low history length with only singular exceptions at higher history length. As with the first experiment, a variation of benefits for each history length can be observed, demonstrating the effect of unwisely chosen parameters. The few points with very good benefit at high history are found due to a specific characteristic of the heuristic algorithms. These algorithms tend to over adjust parameters, i.e., they find parameters that are optimized for one specific case the algorithm is run on and that are not useful in any other situation. These single values can therefore be ignored.

Figure 4.7 lastly shows the result when combining **direct trust, confidence and reputation (DTCR)**. The same trend of lower history length for greater benefit persists here as well. As with the first experiment, the reputation reduces the variation of benefits at each history length.

A first difference to observe is the absence of low benefit results for small history length, even on the DT and DTC metrics. To turn to this effect, another ADSE was conducted, but this time with a fixed history length of 2. Figure 4.8 shows the results of the experiment, depicting the minimal and maximal cumulative benefit per metric. As reference, the benefit of the **random (RAND) metric** (4871), which picks an agent randomly in every time step, is depicted as well.

Here a major difference to the first experiment is seen. The best and worst results for all metrics are about the same. They only vary insignificantly. When looking at the values that were chosen for the parameters of Table 3.1, w_v (the weight of the confidence metric) tended towards high values, hence the variance is an important aspect. As was shown in Appendix A, a variance value based on {0,1}-values is always maximal, so therefore one would expect the variance to not be important. The answer to that also explains the difference to the continuous experiment. Based on binary experience values and a history length of 2, only three possible trust values t_{direct} exist (based on the experience ratings r):

- $t_{direct} = 0$ if $r = (0, 0)$
- $t_{direct} = 0.5$ if $r = (1, 0)$ or $r = (0, 1)$
- $t_{direct} = 1$ if $r = (1, 1)$

Also, only two possible variations for an experience exist, either 0 or 1. So when choosing a random agent, the chance to get a 1 is calculated based on the mean value of each agent. Considering the agent types described in the first section and using a mean distribution to choose the actual mean value for a specific agent the mean value of each interval is used to estimate the result of random:

- Type 1 has a mean value of 0.8, providing 30 agents.
- Type 2 has a mean value of 0.6, providing 40 agents.
- Type 3 has a mean value of 0.45, providing 20 agents.
- Type 4 has a mean value of 0.25, providing 10 agents.

The mean value also is the chance to get a 1 from an agent, so the chance per timestep to get a 1 when picking randomly is $0.8 * 30 + 0.6 * 40 + 0.45 * 20 + 0.25 * 10 = 0.595$. The experiment ran for 8000 timestep so the expected average result of the random selection metric is $8000 * 0.595 = 4760$. The observed result of 4871 was only about 2.3% off. A small deviation was to be expected, since the variance of each agent was not considered to simplify the calculation of the expected result.

Considering only the last two experiences, an adequate prediction can be done for the next transaction. The closer the mean value is to the extremes of 0 and 1, the better the prediction, since a longer chain of zeros and ones is required to obtain that mean value, e.g., mean value $0.9 = \frac{9*1+1*0}{10}$. The goal is to find agents with a high mean value and avoid agents with a low mean value, so this prediction is especially well-suited.

This also explains why a high weight was chosen for the confidence variance. If a trust value of 0 or 1 was calculated, the variance confidence is 1 (variance of 0). Since all considered experiences had the same rating, one can expect the next experience to be the same. The only other value, 0.5, results in a confidence variance of 0 (variance maximal). In this case the prediction of the next experience has the highest uncertainty so it is the best to ask others, i.e., include reputation.

A noticeable difference to the experiment with continuous experience ratings is on the one hand the much higher cumulative benefit at low history length and a lower cumulative benefit at higher history length. Since an experience can only be good (rated as 1) or bad (rated as 0), a mean value can be misleading. An exception are the mean values of 0 and 1 as was explained above. All other values just mark uncertainty about the interaction partner and how good the next interaction will be. The evaluation has shown that adding several grades of uncertainty does not add more information, especially since they also increase the time until a change of behavior is identified. When the diversity of uncertainty gets too high, i.e., too many mean values between 0 and 1, the cumulative benefit even drops below the achieved benefit of the continuous experiment.

Having a binary rating system for experience increased the total benefit and is therefore preferred to a continuous rating system, but how experiences can be rated is application specific. The Delayed-Ack Algorithm logically rates messages binary (received or not received) while the Energy Grid rates a prediction of power production. The further the prediction is off from the actual production, the worse the prediction which is naturally a continuous rating.

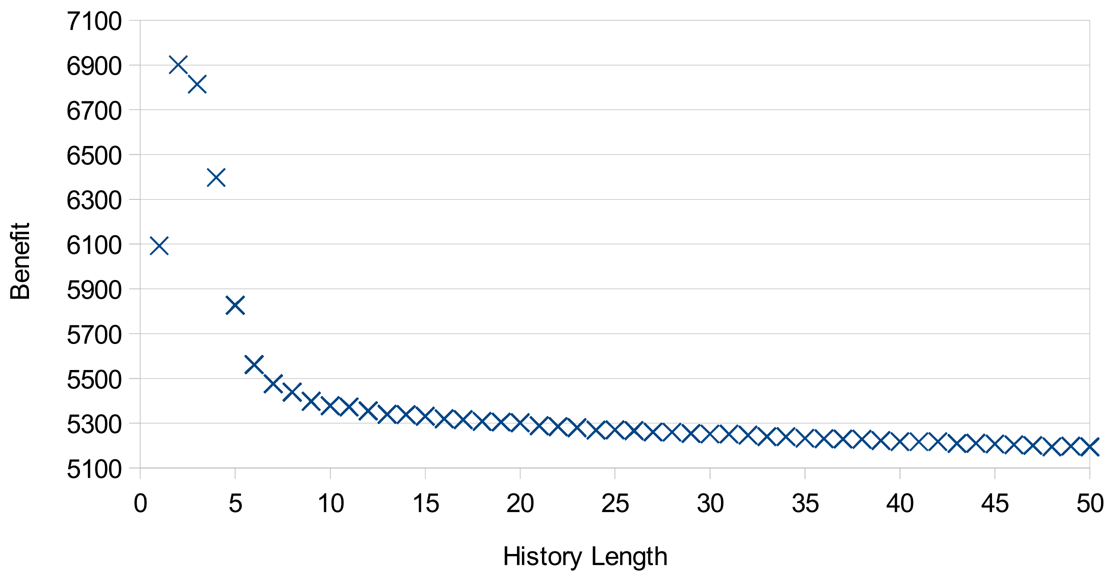


Figure 4.5.: Benefit versus history length for selection metric direct trust (DT) using binary experience ratings (8 behavior changes)

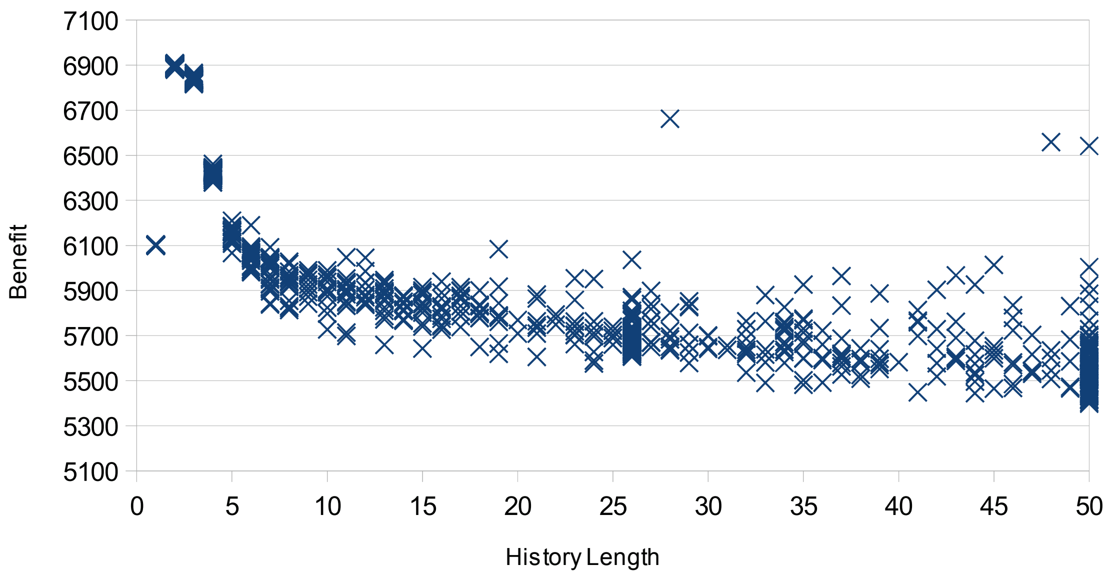


Figure 4.6.: Benefit versus history length for selection metric direct trust and confidence (DTC) using binary experience ratings (8 behavior changes)

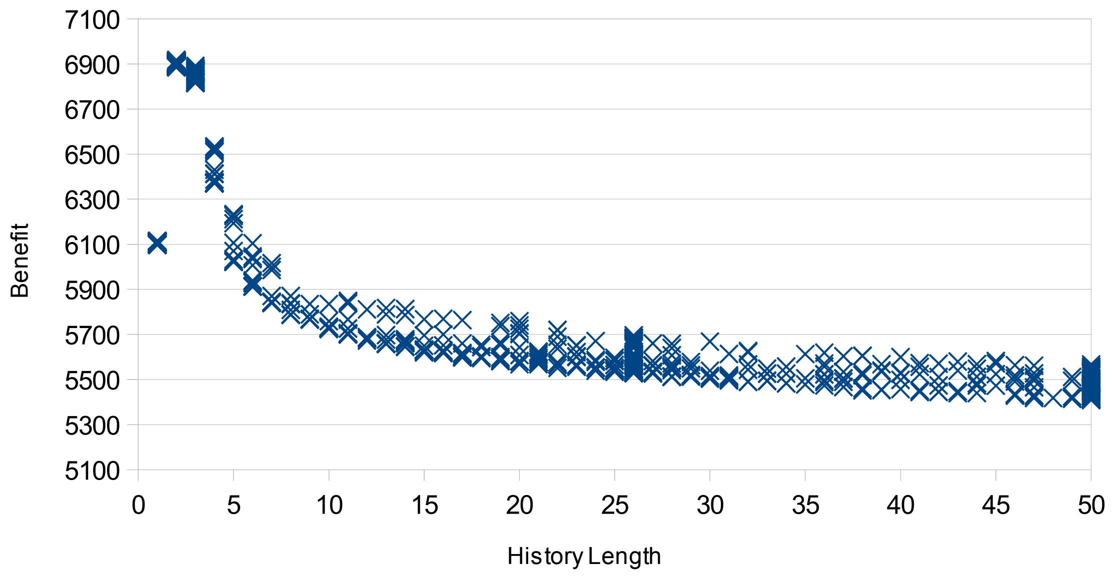


Figure 4.7.: Benefit versus history length for selection metric direct trust, confidence, and reputation (DTCR) using binary experience ratings (8 behavior changes)

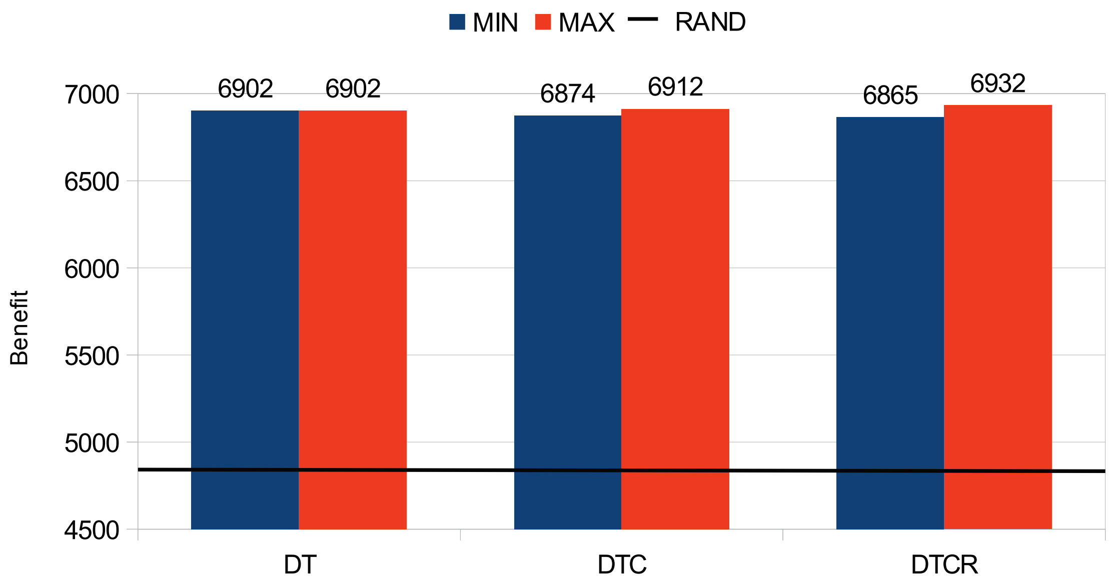


Figure 4.8.: Best and worst results for each selection metric in comparison with random (RAND) for history length 2 when using binary experience ratings (8 behavior changes)

4.4. Scenario with Few Behavior Changes

In this section the amount of behavior changes is reduced, yet not completely removed. Behavior changes are conducted after 2000 and then again after another 4000 time steps. The last 2000 time steps contain no more behavior changes. In total, only 2 behavior changes are done within this scenario. Again both continuous as well as binary experience ratings are investigated.

4.4.1. Continuous Experience Ratings

First the results for continuous experience ratings are presented. As before every experience is rated with a value between 0 and 1.

Figure 4.9 depicts the results if only **direct trust (DT)** is used to decide the next interaction partner. The characteristics of the curve is similar to the preceding experiment. A lower history length is preferable to a higher history length. The difference to before is, that a history length of 3 results in about the same, if not slightly higher, cumulative benefit as a history length of 2.

Figure 4.10 depicts the cumulative benefit for different history lengths when using **direct trust with confidence (DTC)** to select the next interaction partner. The results for this metric are widely different than the other experiments so far. Compared to them, the history length is not the dominating factor, instead a high variance of good cumulative benefit values can be observed up to history length 30. Since the behavior of each agent is stable most of the time, a fast adjustment is not essential here, leaving the history length with strongly reduced influence on the total result. Instead, the configuration of the other parameters is more important to obtain a good cumulative benefit.

Figure 4.11 depicts the results when using all three parts of the trust metric, i.e., **direct trust, confidence, and reputation (DTCR)**. Here the history length is again the dominating factor. Similar to using only direct trust, but contrary to the experiments with 8 behavior changes, the highest cumulative benefit is achieved with history length 3 and not with 2.

Since a history length of 3 seems to create better results than a history length of 2, the best and worst possible configurations for both history length 2 and 3 are investigated. The baseline selection metric **random (RAND)** achieved a cumulative benefit of 4871.

Figure 4.12 shows the best and worst cumulative benefit that were found by ADSE for history length 2. The results are similar to the experiment with 8 behavior changes. That is adding confidence (DTC) or reputation (DTCR) can result in a better cumulative benefit than direct trust (DT) alone. But the DTC metric also allows for a worse cumulative benefit, if an unwisely set of parameters are chosen, while adding reputation with the DTCR metric evens out bad parameter configurations with the lowest found result being higher than with direct trust alone. The best found result for DTC and DTCR are similar.

Increasing the history length to 3 yields interesting results, see Figure 4.13. For one, the cumulative benefit is generally higher with all metrics, which is to be expected when looking at the experiments with variable history length. The most notable difference though is the strong increase of the best possible value for direct trust, increasing it even beyond the best possible value for the DTCR metric.

A statistical analysis showed some interesting effects:

- **Number Confidence:** Due to the low number of considered past experiences, i.e., low history length, the number confidence had very little influence. Its weight to the total confidence value showed no trend in the analysis.
- **Age Confidence:** An experience was aging fast, i.e., dropping below 1 for its actuality rating, in both metrics (τ_r tended to low values). The threshold, when to consider it out of date (τ_o) showed no real trend, but was in the higher half of the domain for the DTCR metric. Its weight showed no trend in the DTC metric and was low in the DTCR metric.
- **Variance confidence:** While the weight of the variance metric showed no trend in the DTC metric, it tended to higher values in the DTCR metric.
- **Reputation metric:** Here an interesting effect occurred. Both thresholds tended to high values, with τ^* set near the maximum of the domain. This means that even a considerable deviation from a recommendation to ones own experience is still considered good enough for a positive adjustment of the participant that gave the recommendation.
- **Aggregation metric:** The parameters for the aggregation metric were chosen to mostly use reputation only: τ_{cl} tended high with τ_{ch} near the maximum of the domain. The result was a system that is similar to web reputation systems, e.g, the ebay reputation metric. They often take decisions based on the experience of others. Since the system is in a mostly stable state, i.e., nearly no behavior changes, a combination of the knowledge of others was an acceptable basis to choose the next interaction partner.

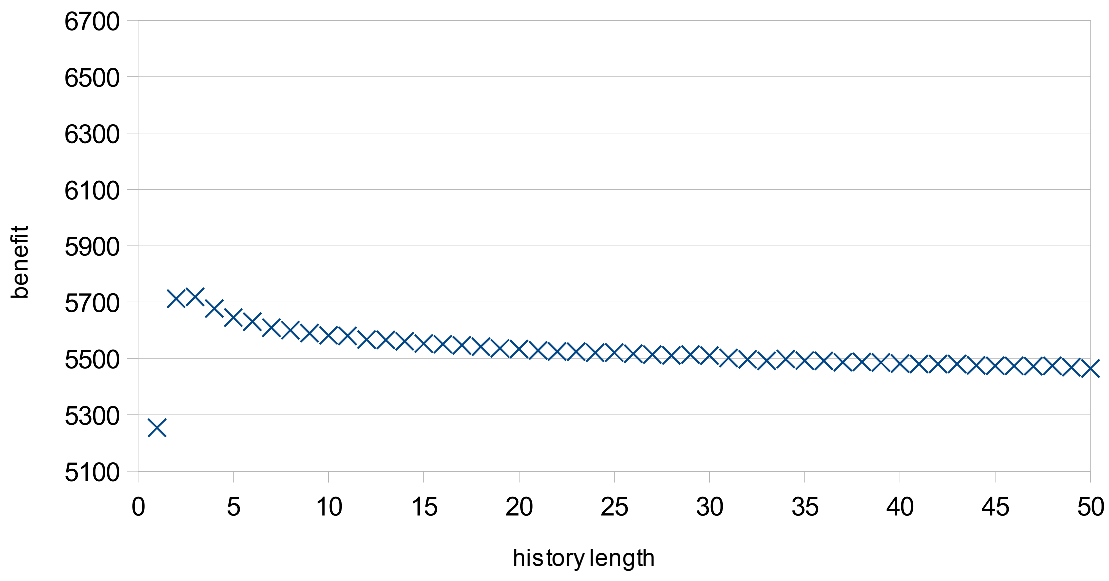


Figure 4.9.: Benefit versus history length for selection metric direct trust (DT) using continuous experience ratings (only 2 behavior changes)

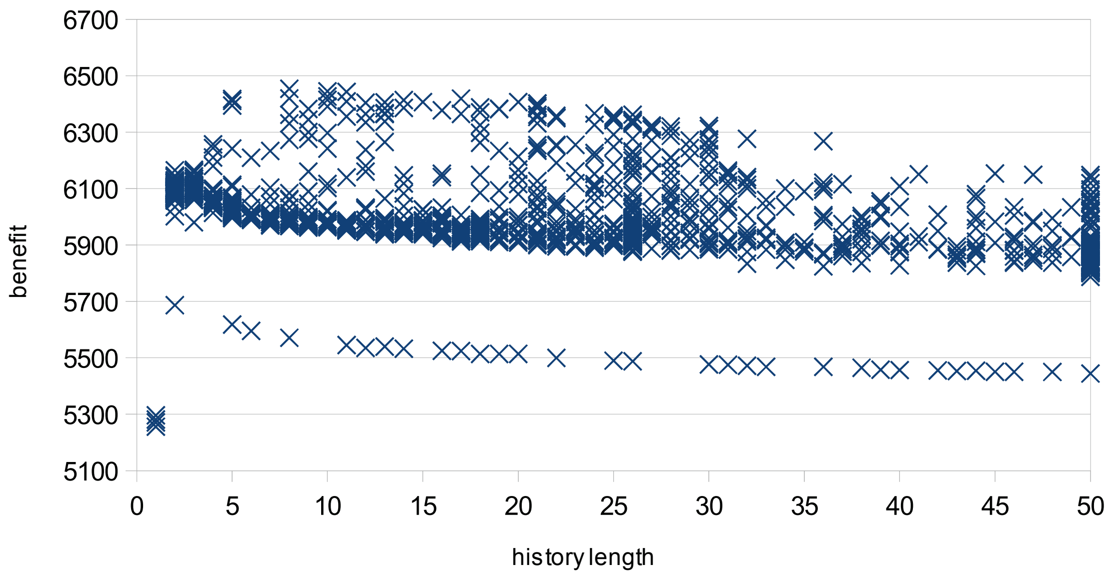


Figure 4.10.: Benefit versus history length for selection metric direct trust and confidence (DTC) using continuous experience ratings (only 2 behavior changes)

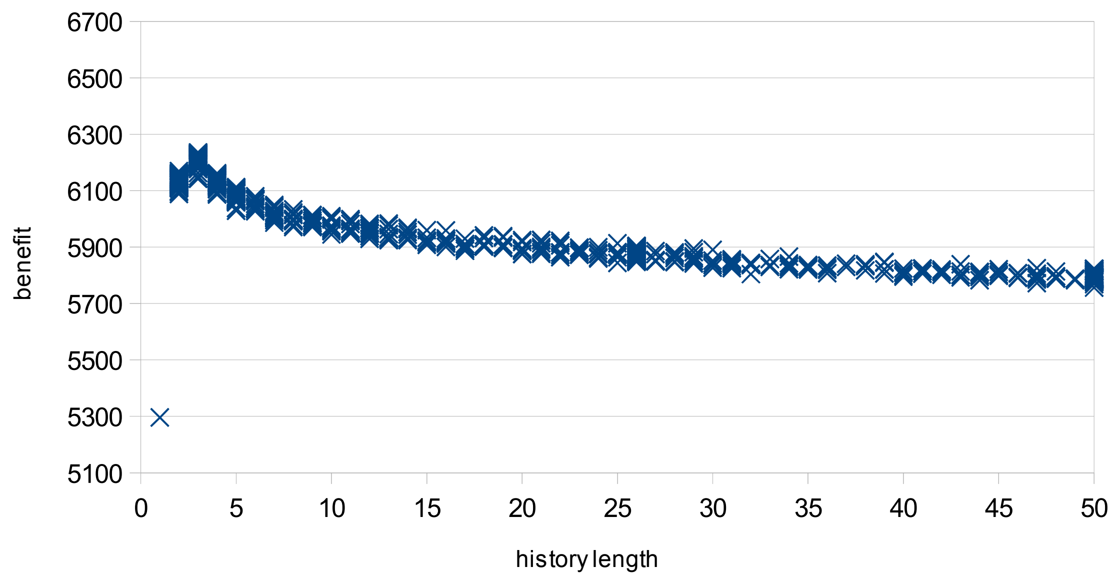


Figure 4.11.: Benefit versus history length for selection metric direct trust, confidence, and reputation (DTCR) using continuous experience ratings (only 2 behavior changes)

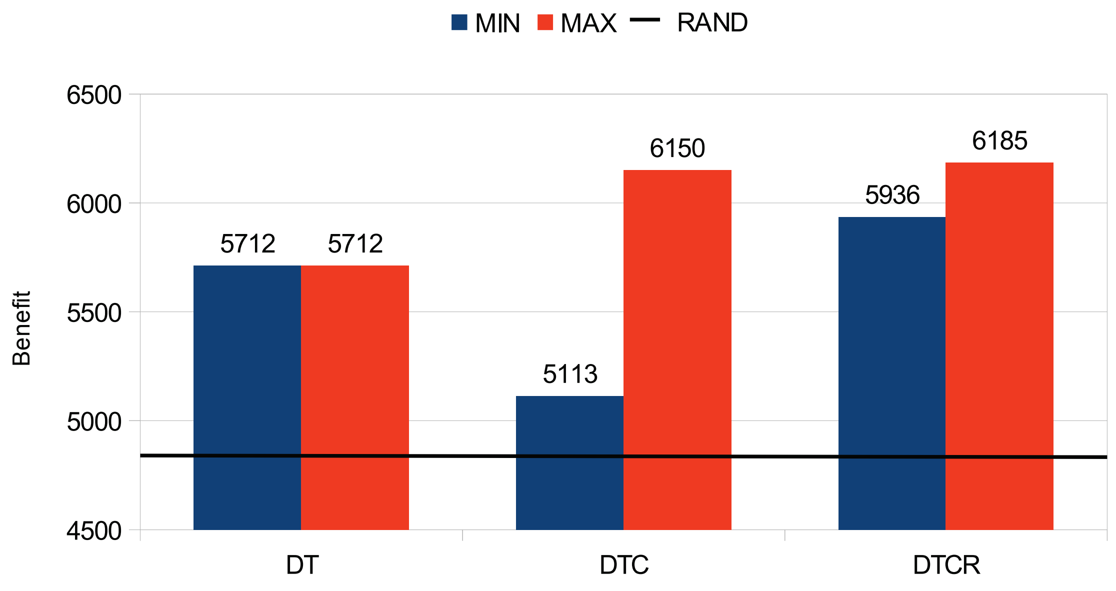


Figure 4.12.: Best and worst observed results for each selection metric in comparison with random (RAND) for history length 2 when using continuous experience ratings (only 2 behavior changes)

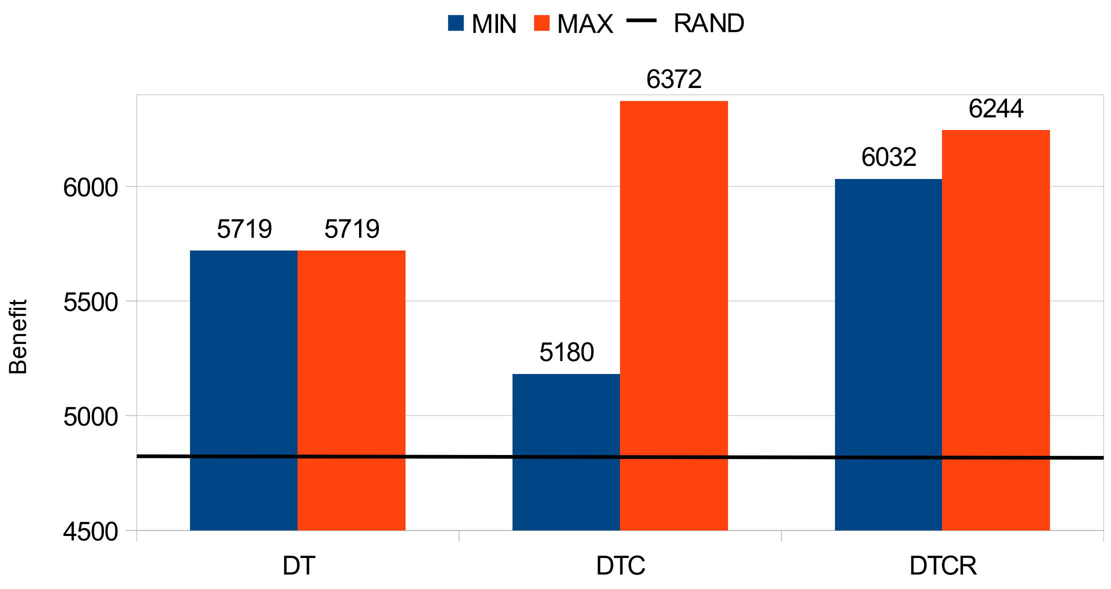


Figure 4.13.: Best and worst observed results for each selection metric in comparison with random (RAND) for history length 3 when using continuous experience ratings (only 2 behavior changes)

4.4.2. Binary Experience Ratings

As comparison, this experiment uses binary experience values, i.e., experiences are rated as either 0 or 1. Otherwise the experiment is identical to the continuous variant with only a total of 2 behavior changes.

Figure 4.14 depicts the result for the **direct trust (DT)** selection metric. Here the history length is again the dominating factor, with a maximum cumulative benefit at history length 2.

Figure 4.15 depicts the results when adding **confidence to direct trust (DTC)** when selecting a suitable interaction partner. Similar to the continuous experiment, the results show some high benefit values at higher history length, but with less variance. Nonetheless lower history length is preferable, since no low results were observed while having the highest result at low histoy length.

Adding **reputation to direct trust and confidence (DTCR)**, see Figure 4.16, reduces the variance of the results. Here the impact of a low history length is again prevalent. The best results are again observed with history length 2.

Since a history length of 2 seems to be the best choice, all selection metrics were examined with a fixed history length of 2. The results are depicted in Figure 4.17. **Random (RAND)** was again used as baseline with an achieved cumulated benefit of 4886. The results are similar to the experiment with binary experience values and 8 behavior changes. The minimum and maximum achieved cumulative benefit values are similar. In addition, not much can be gained by adding confidence and reputation.

As comparison with the continuous results, Figure 4.18 depicts the best and worst found parameter set for a fixed history length of 3 instead of 2. The best found parameter set for the DTC metric is slightly higher with a history length of 2, showing a similar trend as the continuous case. But typical for the experiments with binary experiment ratings, the minimal and maximal found benefit values differ only slightly. Additionally, the benefit values found with the DTCR metric are better with history length 2 than with 3. So in total, history length 2 is preferable in the binary case.

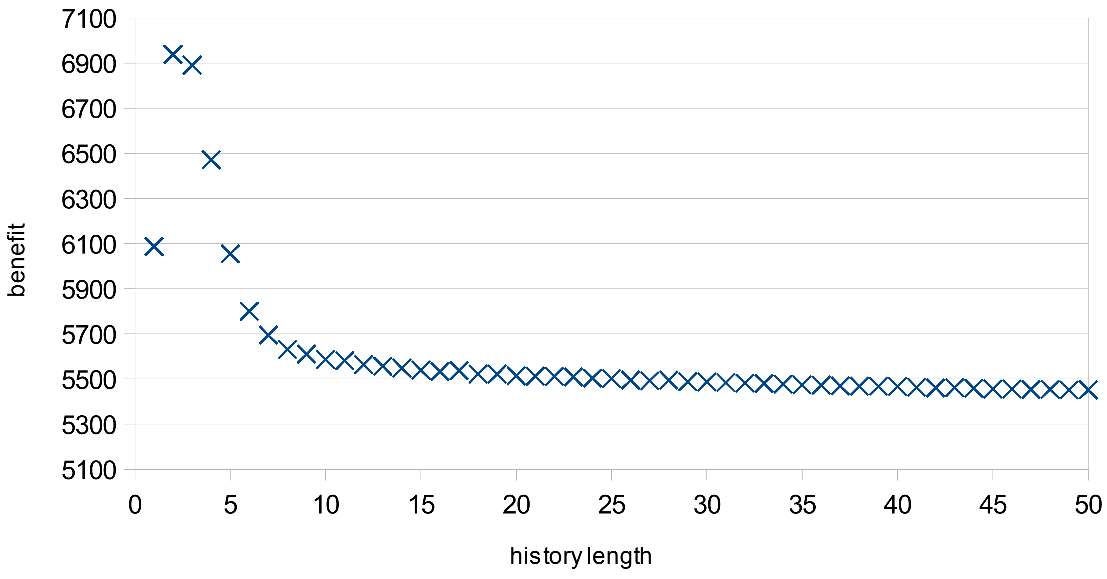


Figure 4.14.: Benefit versus history length for selection metric direct trust (DT) using binary experience ratings (only 2 behavior changes)

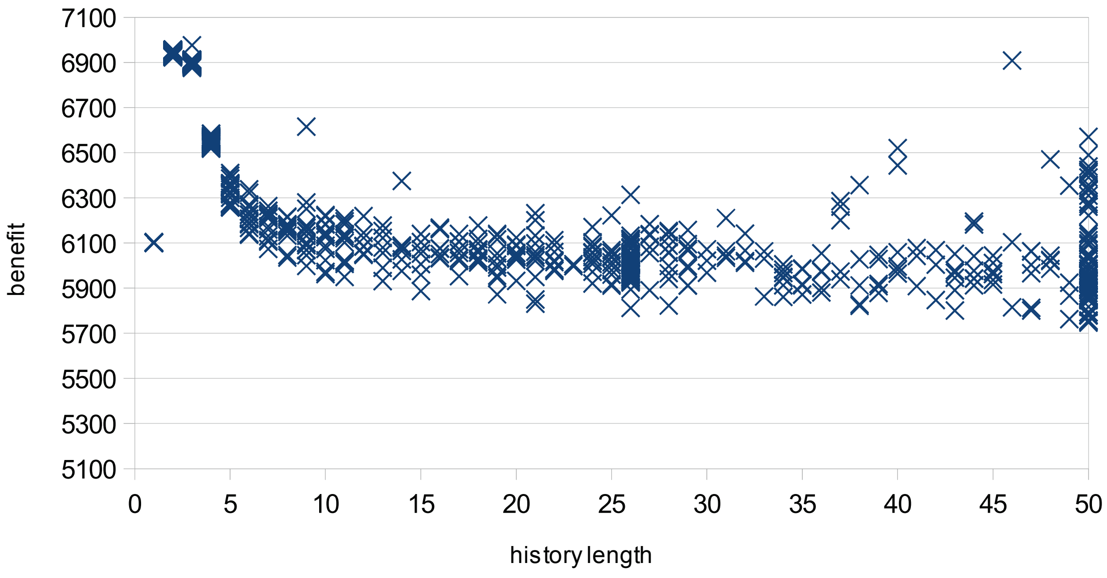


Figure 4.15.: Benefit versus history length for selection metric direct trust and confidence (DTC) using binary experience ratings (only 2 behavior changes)

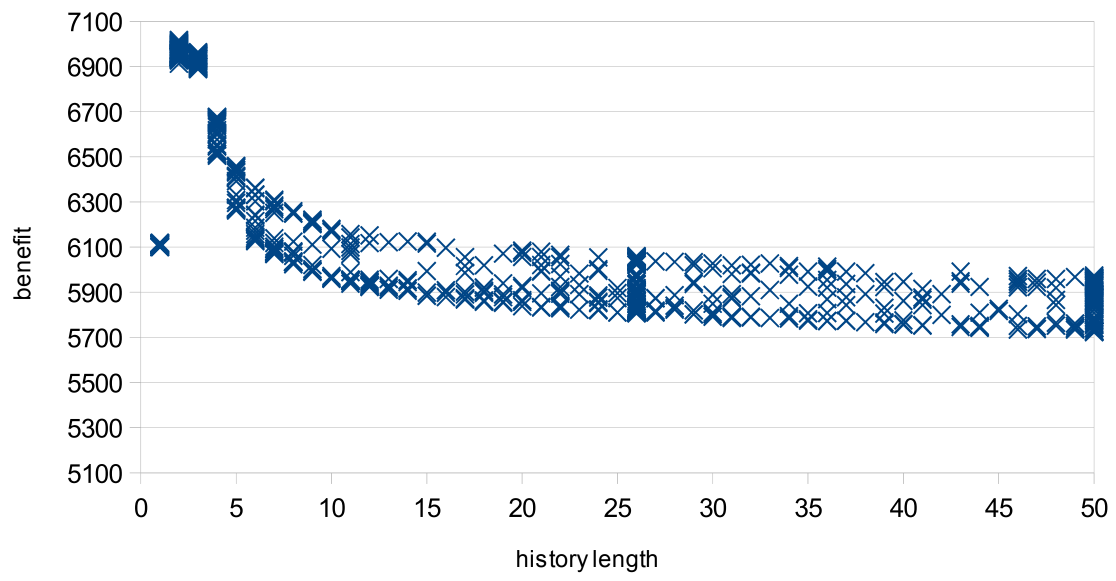


Figure 4.16.: Benefit versus history length for selection metric direct trust, confidence, and reputation (DTCR) using binary experience ratings (only 2 behavior changes)

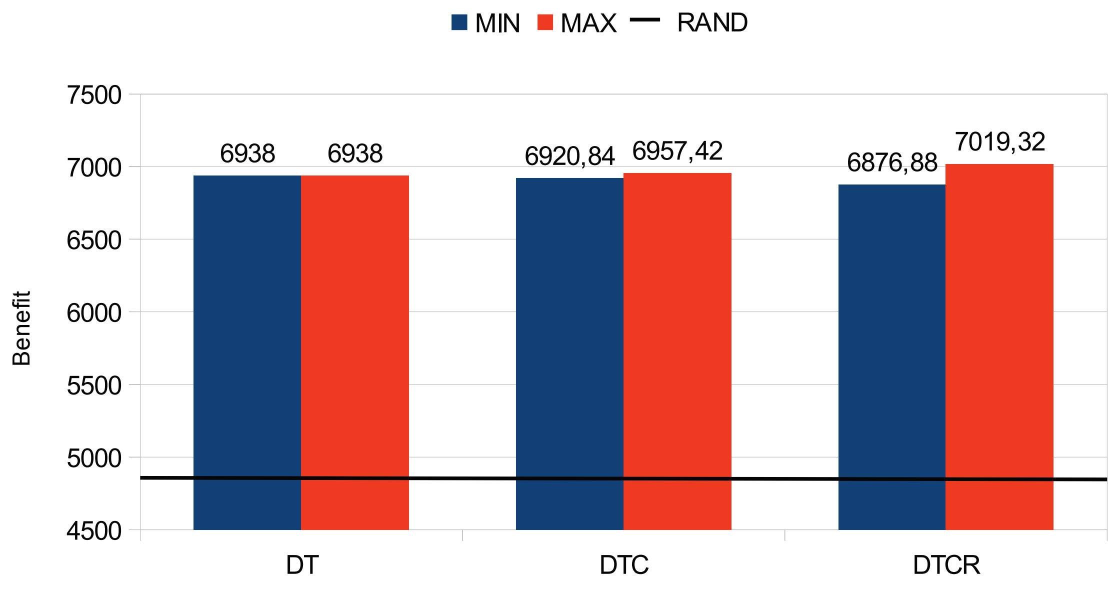


Figure 4.17.: Best and worst observed results for each selection metric in comparison with random (RAND) for history length 2 when using binary experience ratings (only 2 behavior changes)

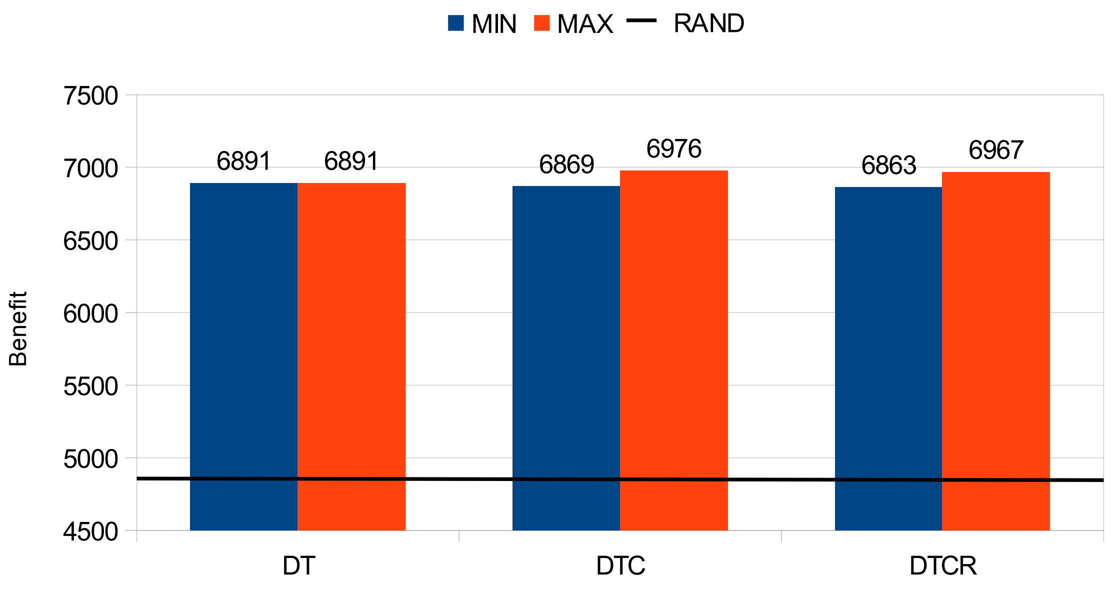


Figure 4.18.: Best and worst observed results for each selection metric in comparison with random (RAND) for history length 3 when using binary experience ratings (only 2 behavior changes)

4.5. Scenario with Frequent Behavior Changes

This scenario features a lot of behavior changes, happening every 50 time steps. This leads to a total of 160 behavior changes during the evaluation. Both continuous and binary experience values are investigated. The evaluation system is constructed as the systems before, just with the difference of more behavior changes, evaluation a highly volatile system that is hard to predict. An example could be a solar power plant, when a lot of clouds are moving to mask and unmask the sun regularly. The prediction of said power plant will probably be more and less off, depending if clouds are masking the sun at the moment or not.

4.5.1. Continuous Experience Ratings

At first, the results for continuous experience ratings are investigated.

Figure 4.19 depicts the results with the **direct trust (DT)** selection metric. On the one hand, the typical characteristic of the results can be observed again, that is, the advantage of a lower history length with the optimum at history length 2. On the other hand, the total cumulative benefit, even at history length 2, is significantly lower than with the other experiments. This effect is a result of the volatile nature of the agents, switching their behavior every 50 time steps. As a result, the interaction partner has to be changed a lot when its behavior changes for the worse, leading to some bad experiences each time.

Figure 4.19 depicts the result when using only **direct trust (DT)**. Similar to the other experiments, a low history length is preferable again. the biggest difference to the other evaluations is the significantly lower benefit that is achieved for every history length. This happens due to the volatile nature of the system, when a behavior change often results in some bad experiences until the system adapts.

Figure 4.20 shows the results when using **direct trust with confidence (DTC)**. In contrast to the evaluation with only 2 behavior changes but similar to the first experiment, the results show again the typical characteristics of preferably lower history length. While the highest cumulative benefit is higher than with only direct trust, it is still lower than with the other experiments. This is to be expected due to the volatile nature of the agents.

Figure 4.21 depicts the results when using all parts of the trust metrics, i.e., **direct trust, confidence, and reputation**. The variance for each history length is strongly reduced compared to DTC, while still achieving similar good results for low history length.

To compare the effectiveness of each selection metric, the best and worst possible configuration for history length 2 was searched for. Similar to the other experiments, history length 2 provided the highest cumulative benefit. Figure 4.22 depicts the best and worst found benefit values for each selection metric. **Random (RAND)** as baseline achieved a cumulative benefit of 4997. All metrics are significantly better than random selection. It also shows that the DTC metric provided better results than the DT metric. If the other 12 parameters are chosen unwisely, the result is as lows as with the DT metric. Adding reputation increases the minimal found cumulative benefit, while retaining the good results of DTC.

Some parameters showed definite trends on a statistical analysis:

- **Number Confidence:** Due to the low history length, the amount confidence naturally featured a low value for w_n, i.e., the confidence reached 1 very fast. For DTC, it was weighted very highly for the total confidence, while the opposite happened for DTCR.
- **Age Confidence:** Both the DTC and DTCR metric favored a parameter choice to swiftly let the actuality rating of an experience drop below the maximum (low τ_r) but with a significant time until they are marked as outdated (middle to high τ_o). For DTC the amount confidence was rated very low for the total confidence while the DTCR metric preferred a low to middle weight.
- **Variance confidence:** The variance confidence showed no trend for both DTC and DTCR.
- **Reputation metric:** The reputation metric was parametrized to feature a very small area for a positive match (low τ threshold) but with a high area until the recommendation is adjusted negatively (high τ^*). The maximal adjustment was also set very high, so a false recommendation was punished strongly. This reinforces the observed effect, that fast change to behavior is important in such a volatile system.
- **Aggregation metric:** For the aggregation the thresholds for the confidence were chosen wide apart, creating a big range, where the total trust value is shifted from reputation to direct trust. It was preferable to nearly always include both parts in the total trust value.

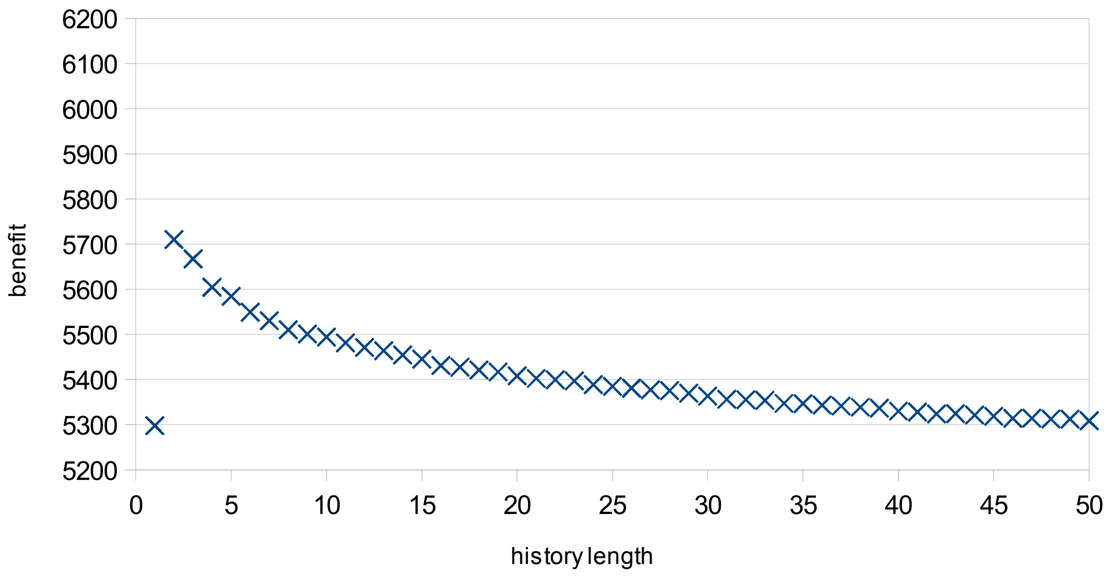


Figure 4.19.: Benefit versus history length for selection metric direct trust (DT) using continuous experience ratings (behavior changes every 50 time steps)

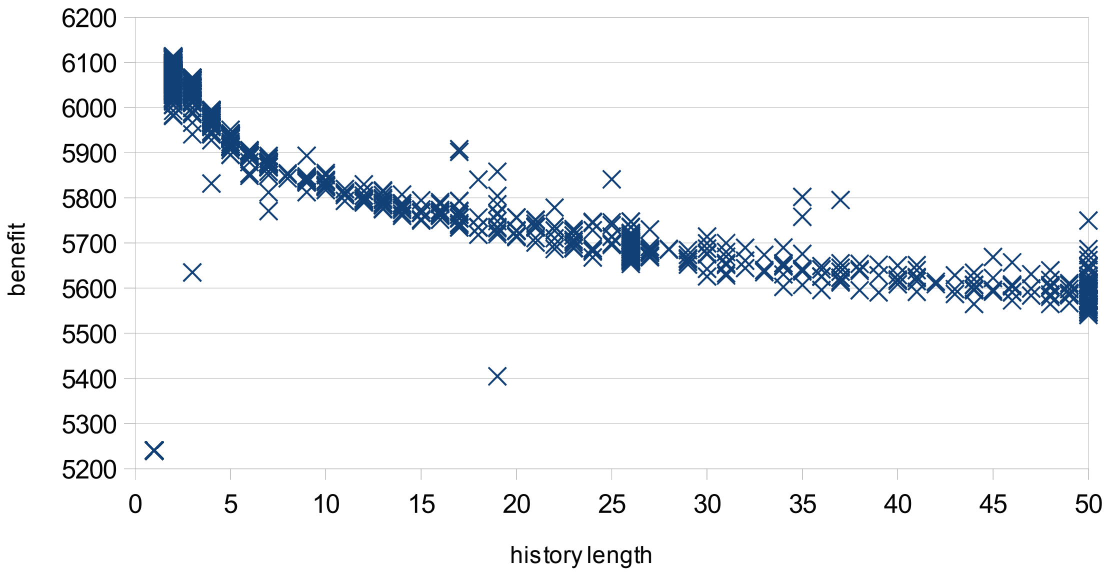


Figure 4.20.: Benefit versus history length for selection metric direct trust and confidence (DTC) using continuous experience ratings (behavior changes every 50 time steps)

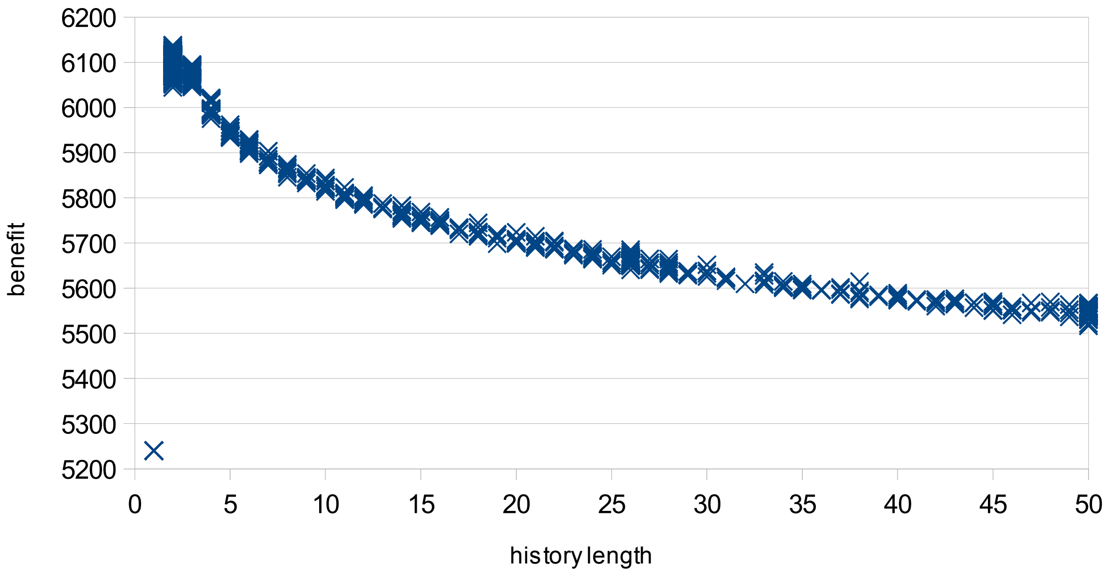


Figure 4.21.: Benefit versus history length for selection metric direct trust, confidence, and reputation (DTCR) using continuous experience ratings (behavior changes every 50 time steps)

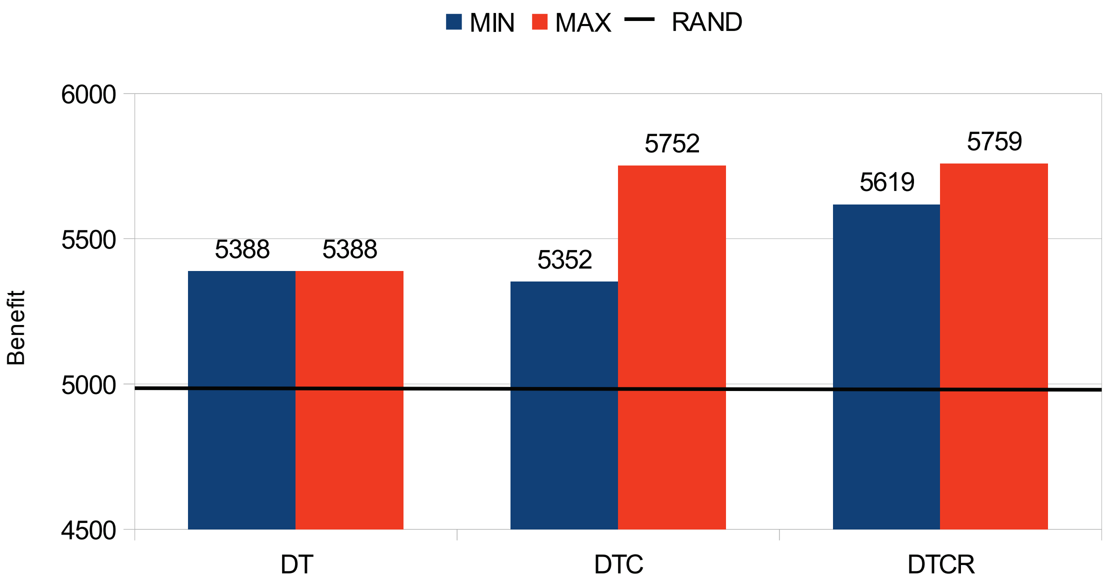


Figure 4.22.: Best and worst observed results for each selection metric in comparison with random (RAND) for history length 2 when using continuous experience ratings (behavior changes every 50 time steps)

4.5.2. Binary Experience Ratings

The last experiment was run with binary experience ratings but still 160 behavior changes.

Figure 4.23 depicts the results for the **direct trust (DT)** selection metric. The positive effect of low history length can be clearly seen, with the maximum at history length 2 yet again. The best parameter set found results in a cumulative benefit that is higher than with continuous experience ratings. But it is also lower than the achieved cumulative benefits of the other experiments with binary experience ratings. It is therefore consistent with the continuous experiment that showed similar results, i.e., the volatile nature of the agents lowers the achievable benefit. One big difference to all other experiments can be observed, though: The achieved cumulative benefit for history length 1 is quite high and one of the better points. Since the system is highly volatile of its behavior, a fast adjustment to change is required, which also explains the strong increase in benefit when getting to the lower history length values. Due to the high necessity of a fast behavior change adjustment and the fact, that an experience can only be of two types (good or bad), a history length of one provided acceptable results. Nonetheless, a meaningful, i.e., non trivial, mean value is still preferable for the best result.

Figure 4.24 shows the results for the **direct trust with confidence (DTC)** selection metric. Similar to the other experiments, a low history length is preferable. The obtained benefit values show some variation on higher history length depending on the chosen values for the other 12 parameters. Also, similar to the DT metric, the achieved cumulative benefit for history length 1 is quite high and does show no deviation. The missing deviation can be explained, since most metrics are based on some kind of mean value, which can not deviate based on only one single value.

Figure 4.25 shows the results, if all trust metric parts, i.e., **direct trust, confidence and reputation (DTCR)**, are used in conjunction. It shows the typical characteristics of preferable low history length while negating the variation of DTC. Yet again, the result for history length 1 is quite high.

To conclude, Figure 4.26 shows a direct comparison of each selection metric (DT, DTC, and DTCR) for history length 2, which has proven to be the optimal value, overshadowing the other 12 parameters. For each selection metric the minimal and maximal found benefit are displayed, as well as the benefit obtained by **random (RAND)** selection (4872). All minimal and maximal values are close to each other while being significantly better than random selection, which is consistent with the other binary experiments. The generally lower benefit values are due to the volatile system with 160 behavior changes. Therefore several more bad interactions each time the system needs to adapt are experienced, leading to a generally lower total result.

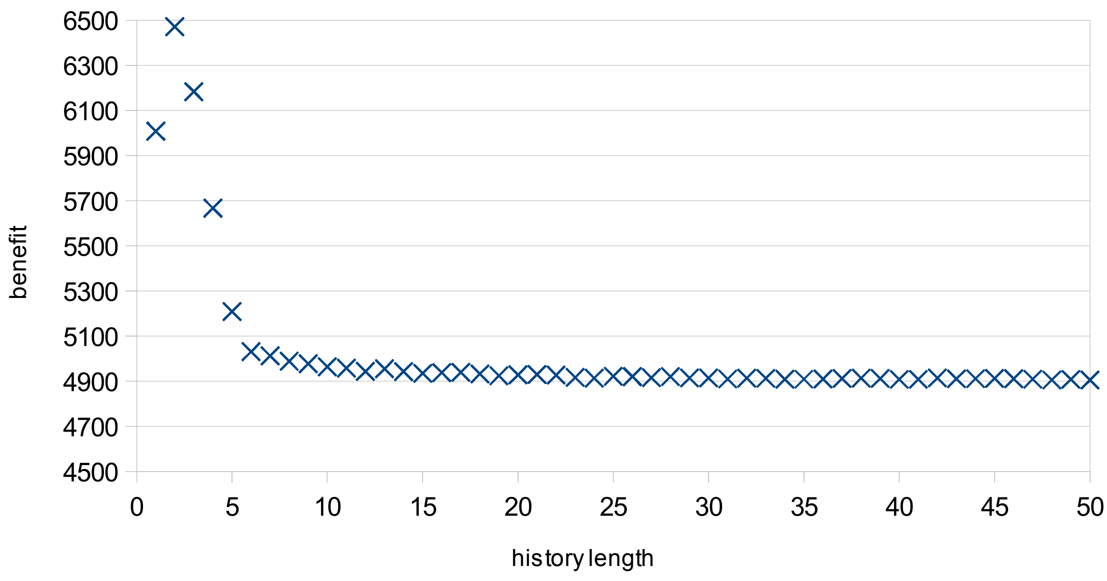


Figure 4.23.: Benefit versus history length for selection metric direct trust (DT) using binary experience ratings (behavior changes every 50 time steps)

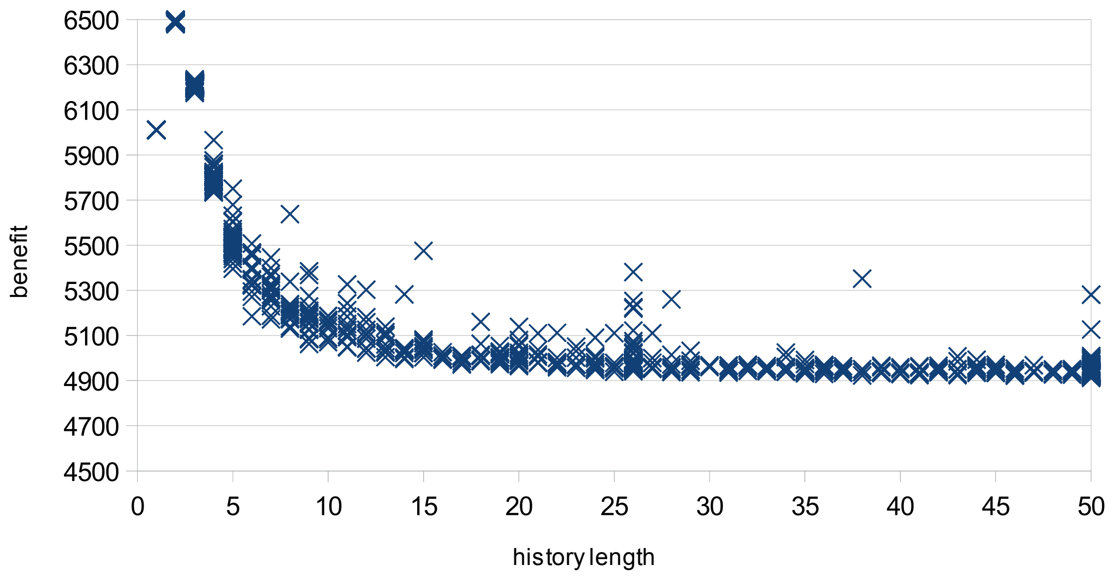


Figure 4.24.: Benefit versus history length for selection metric direct trust and confidence (DTC) using binary experience ratings (behavior changes every 50 time steps)

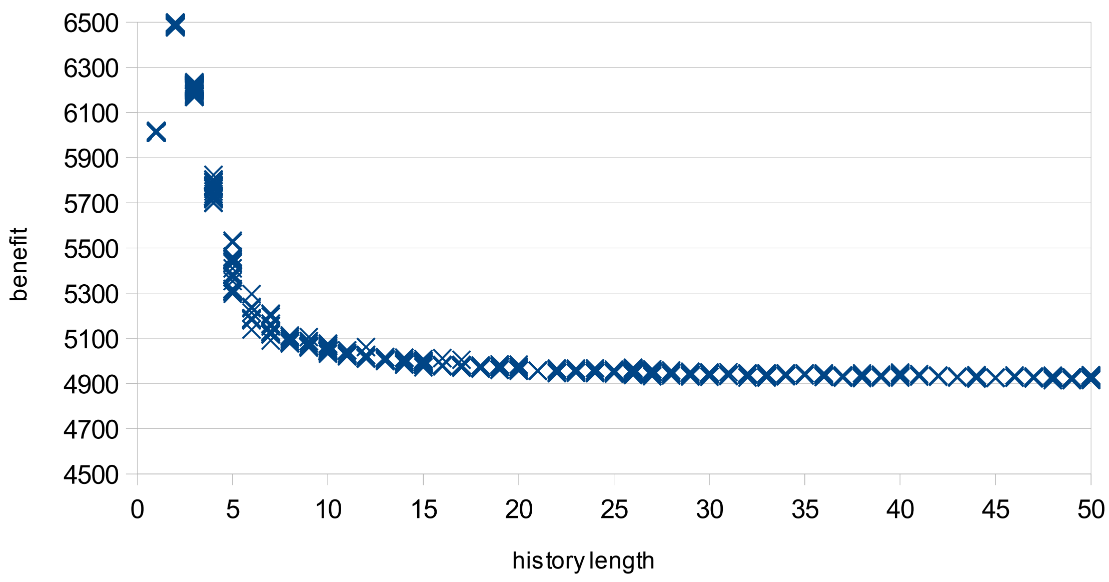


Figure 4.25.: Benefit versus history length for selection metric direct trust, confidence, and reputation (DTCR) using binary experience ratings (behavior changes every 50 time steps)

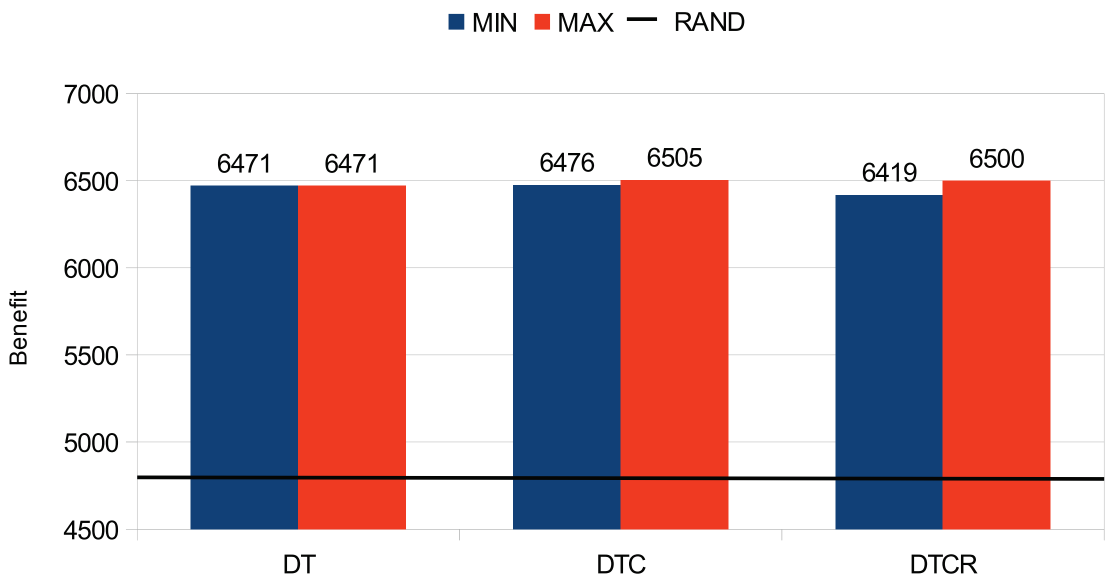


Figure 4.26.: Best and worst observed results for each selection metric in comparison with random (RAND) for history length 2 when using binary experience ratings (behavior changes every 50 time steps)

5. Trust-Enabling Middleware (TEM)

To make the trust metrics described in Chapter 3 available for a wide variety of applications the **Trust-Enabling Middleware (TEM)** [1] was designed. The goal of the TEM is to provide a prototypical implementation of an distributed organic system that provides the aforementioned trust metrics. Each instance of the TEM middleware represents a logical node in a distributed system, which can be a grid system or a Multi-Agent-System (MAS). The TEM was enhanced with MAS concepts in the OC-Trust research group to the **Trust-Enabled Multi-Agent-System (TEMAS)** [1].

The TEM as basis of the TEMAS serves as basis for all kinds of applications, which can be registered and run on the TEM. These services define the functionality available. In turn, the TEM provides the following capabilities for every service:

- Sending and receiving messages with logical node IDs. The middleware executes the actual message sending on lower level.
- Monitoring of the message flow. Each service can register monitors in the TEM, which are able to monitor all incoming (from a node to services) and outgoing (from services to other nodes) messages.
- Piggybacking additional information on application messages. With the aforementioned monitors additional data can be added to application messages, e.g., which is used by the Delayed-Ack algorithm (see Section 3.1) to identify whether the messages were received.
- Saving experiences and calculating direct trust and reputation. The TEM provides all the metrics described in Chapter 3, which in turn can be utilized by the services. The architecture of the so called **trust metric infrastructure** is described in Section 5.3.

Each service can be in one of three states, depicted by Figure 5.1.

- **Unregistered**: Such a service is just instantiated but not yet registered on a node. It can neither receive messages nor generally participate in the system in any way.
- **Inactive**: The service is registered on a node. A message queue is created and all messages for the service are stored in it. They are not sent to the service until it is active.

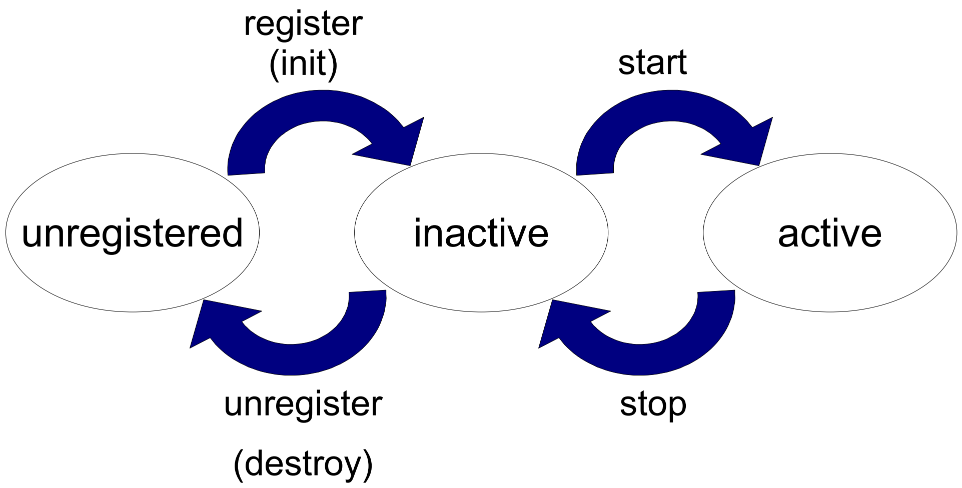


Figure 5.1.: Life-cycle of a service

- **Active**: The service is now fully functional and can communicate and receive messages normally.

5.1. Architecture

The TEM is a multi-tier middleware system depicted in Figure 5.2. It is based on OCµ [50], a middleware for Organic Computing Systems. In OCµ the left part is the *System under Observation and Control (SuOC)* that is monitored and controlled by the Organic Manager [50][55]. TEM adds trust capabilities to OCµ by adding the `TrustService` as a core service for the trust calculations and will adjust the self-x properties of OCµ by using the collected trust values. Compared to typical self-x property algorithms, especially for self-configuration that only consider load information, trust is an opinion about someone else. This implies that trust information can not be gathered from a node directly, unlike load information, but have to be calculated by others. This significant difference requires new approaches for the self-x properties and are not simple adjustments for already existing algorithms.

A TEM node represents a logical node in a network, usually a PC. The Middleware, the left part of Figure 5.2, consists of three layers:

- **TransportConnector**: This layer handles the communication between nodes. All implementations have to implement the `TransportConnector` interface, abstracting the actual transport layer from the applications. The TEM provides a `LocalTransportConnector`, which handles the transport of messages within the same JVM and therefore enables several logical nodes to run on a single PC. Another important `TransportConncector` is the `JXTATransportConnector`, which

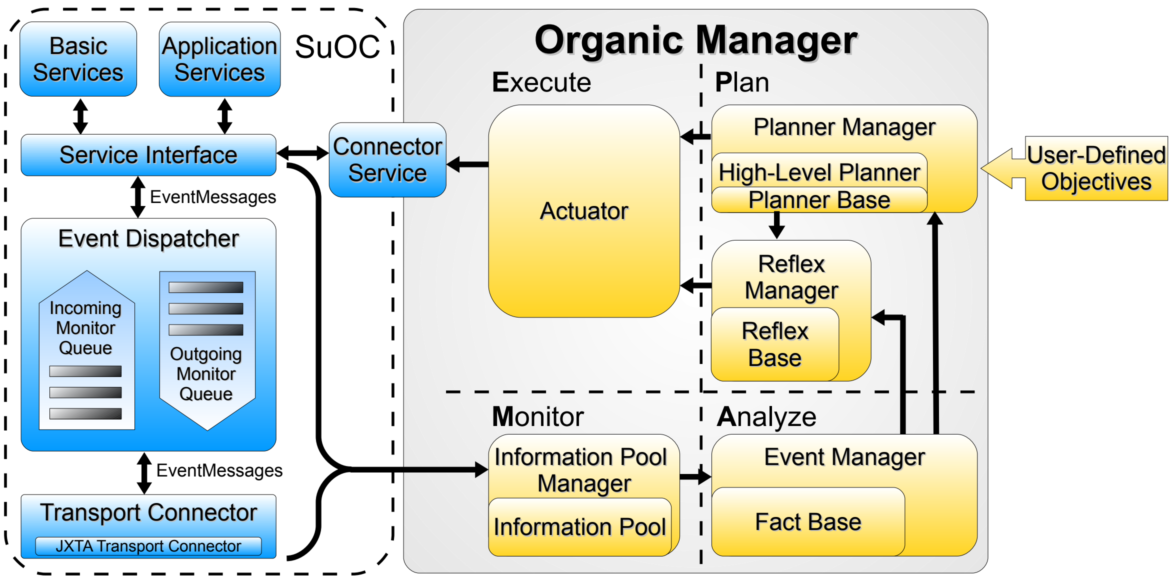


Figure 5.2.: Architecture of OCμ [55]

implements the JXTA Protocol[1], an open source P2P network protocol. With JXTA a P2P network of TEM nodes can be established and therefore communication over a network or even the Internet can be conducted. This enables the TEM to run on any kind of network, if an appropriate `TransportConnector` is provided, while the services run on the TEM do not need to be aware of the underlying network.

- **EventDispatcher**: This layer distributes services to their respective service targets and manages the monitors. On the one hand each received message is delegated from the `TransportConnector` to the `EventDispatcher`, which identifies the services the message is designated to. It also calls every `Monitor` for incoming messages with the given message. On the other hand each service calls the `EventDispatcher` to send a message to another node or service. If the message is designated to a service on another node, it is delegated to the `TransportConnector`, otherwise it is directly assigned to the right service. Similar to incoming messages these outgoing messages are given to the `Monitors` responsible for outgoing messages.
- **Service**: This layer is the actual application layer. Each service that runs on a TEM node needs to implement the `Service` interface. The interface provides the service with all required methods to interact with the middleware. This mainly includes the `ServiceConnector` interface, which provides a set of other interfaces, e.g., to register a monitor, send a message or register the service to receive specific

[1]https://jxse.kenai.com/

messages. The `Service` interface also includes the `processMessage` method, which is called by the EventDispatcher, when a message has to be sent to this service.

```
public interface Service {

 public void init(String serviceId, ServiceConnector serviceConnector,
    Map<String, Serializable> initialData)
    throws InitializationException;

  public void start() throws ServiceStartException;

  public void stop() throws ServiceStopException;

  public void destroy(Map<String, Serializable> transferData);

  public void processMessage(EventMessage message);

  public String getName();

  public String getServiceId();

  public String getServiceType();
}
```

The methods *init*, *start*, *stop*, and *destroy* notify the service about changes in its life-cycle (see Figure 5.1). These methods are called by the TEM when the service state within the TEM changes:

– **init** is called, when the service is registered on a node by the method *registerService*. Messages to the service are saved on the node but not yet delivered.

– **start** notifies the service that it is started, i.e., the *startService* method was called. The service is now running normally.

– **stop** informs the service, that it is suspended but not yet deleted due to the *stopService* method being called on the node. Messages are stored until it is started again.

– **destroy** marks the end of the life-cycle. It is called when the service is removed from a node by calling the *unregisterService* method on the node.

Besides the `Service` interface, additonally a small version of a service, called `Plugin`, is provided. A `Plugin` can be seen as a service without the capability to send and receive messages. This is especially useful for an application that only wants to register Monitors and provide gathered information. The Delayed-Ack Algorithm is implemented in such a manner. Since the Delayed-Ack algorithm only observes the message flow of application messages, the added capability to send and receive messages is not required and would only add overhead.

```
  public interface Plugin {
    public void register(PluginConnector connector);

    public void unregister();

    public String getName();
}
```

Additionally to the application services, a number of basic services are registered on every node automatically when the node is started:

- **RelocatorService**: Provides the functionality to relocate services to other nodes. This service is exclusively called by the self-x property algorithms and is not visible to application services.
- **DiscoveryService**: With this service other services can be located. All appropriate methods are provided by the `Discovery` interface, which can be obtained by the `ServiceConnector`.
- **TrustService**: This service provides the ability to save experiences and calculate trust values. All public methods are provided by the `Trust` interface, the core of the TEM, which is explained in detail in Section 5.3.

To enable the self-configuration to start services on a remote node, or generally enable a remote setup of a node, the `RemoteControl` interface is provided. It provides methods to remotely register, start, stop and unregister a service on any node. The `RemoteControl` interface can be obtained through the TEM node class, so no ordinary service is able to access its methods. Only the self-x property algorithms are supposed to be able to call these methods. Alternatively it can be used for bootstrapping the system. The services are dynamically instantiated by reflection on the target node and then registered.

```
public interface RemoteControl {

    public <I extends Map<String, Serializable> & Serializable>
      String registerServiceOnRemoteNode(
            String fullyQualifiedClassName, I initialData,
            String destinationNodeId, RemoteResult remoteResult);

    public <I extends Map<String, Serializable> & Serializable>
      String registerServiceOnRemoteNode(
            String fullyQualifiedClassName, I initialData,
            Serializable[] constructorData, String destinationNodeId,
            RemoteResult remoteResult);

    public <I extends Map<String, Serializable> & Serializable>
      String registerServiceOnRemoteNode(
            String fullyQualifiedClassName, String serviceType,
            I initialData, String destinationNodeId,
            RemoteResult remoteResult);

    public <I extends Map<String, Serializable> & Serializable>
      String registerServiceOnRemoteNode(
            String fullyQualifiedClassName, String serviceType,
            I initialData, Serializable[] constructorData,
            String destinationNodeId, RemoteResult remoteResult);

    public void startServiceOnRemoteNode(String remoteServiceId,
            String destinationNodeId, RemoteResult remoteResult);

    public void stopServiceOnRemoteNode(String remoteServiceId,
            String destinationNodeId, RemoteResult remoteResult);

    public void unregisterServiceOnRemoteNode(String remoteServiceId,
            String destinationNodeId, RemoteResult remoteResult);
}
```

When calling one of the methods, an instance of the `RemoteResult` interface needs to be given as well. This instance gets acknowledged if the remote action was successful or aborted due to an error. Since the remote operations are asynchronous, requiring messages to be sent to other nodes, the methods of the `RemoteControl` interface are designed as void methods with the `RemoteResult` methods called asynchronously when a return message with the result of the operation arrives. The method `remoteActionSucceded` marks a successful transaction while `remoteActionFailed` is called in case of an error.

```
public interface RemoteResult {

    public void remoteActionFailed(String serviceId, Exception exception,
            String ocmNodeId);

    public void remoteActionSucceeded(String serviceId, String ocmNodeId);
}
```

5.2. Organic Manager

OCμ additionally features an Organic Manager [50][55] to implement the self-x properties. The Organic Manager is based on the MAPE-cycle [31]: **M**onitor, **A**analyze, **P**lan, and **E**xecute. `Monitors` are registered with the `EventDispatcher` to observe the message flow and to distribute load information with piggy-back data on application messages. These raw information are stored in the *Information Pool*. In the next step, the *analyze* phase, this raw information is processed and aggregated into a more high level view, e.g., *high load* instead of the exact amount. The aggregated information is then interpreted by an *Automated Planner* [55] which calculates the necessary steps to regain a stable and optimized system. A step here is the relocation, starting or stopping of a service and the goal is to reach a load balanced system. The planner can be configured by *user-defined objectives*, which define the intended amount of services in the network. The Organic Manager also features a *Reflex Manager* that saves already occurred situations, i.e., unbalanced system states, and the plans, which did correct these situations. If a similar situation appears again, the plan of the Reflex Manager can be immediately executed instead of waiting for the full planner calculations. The actual execution of each step is performed by the *Actuator*. The Actuator has a direct connection to OCµ and is therefore able to send messages to other nodes to realize the service relocations, starts and stops.

The main aspect of the Organic Manager is the automated planner. A planner finds a series of steps to reach a designated goal, in case of OCµ a distributed load of the nodes. The steps to reach that goal can either be the relocation, starting or stopping of a service. The start or stop steps are required, because users can define objectives, like at least 10 services of a specific type have to run in the system. The planner makes sure to start the appropriate amount of services. It also relocates the services to balance the load. While the planner does indeed find suitable solutions for the objectives, its scalability is a problem. A planer searches through the entire planning space, which is constructed as a tree with all possible paths. The nodes of said tree are the steps the system can take. In general the runtime of the planner increases exponentially with the size of the problem. To counter this problem, the Reflex Manager was introduced that caches already calculated plans for further use if a similar situation occurs again.

With the introduction of trust, a planner is not suitable anymore due to its runtime. Trust values are expected to change constantly during the runtime of a system, which would result in repeated misses of the Reflex Manager and therefore constant recalculation of new plans. This also means, that a change in a trust value of a node would trigger the planner again, leading to constant replanning, a high consumption of runtime and long reaction times. For such an ever-changing property like trust a planner is not a suitable tool. Therefore the TEM takes a different approach with integrated basic services for the self-x properties.

5.3. The Trust Metric Infrastructure

The *trust metric infrastructure (TMI)* consists of all interfaces and classes for the trust calculation, Figure 5.5 at the end of this chapter gives an overview of the involved classes. The TEMAS technical report [1] presents an in depth description of the entire system. This chapter will focus on the general structure of the TMI. The `Trust` interface is the entry point for all services to the TMI and provides all required methods for trust calculations. Emphasis was put to support any kind of trust calculation from applications as well as the middleware. Especially the different viewpoints of the middleware and MAS (Multi-Agent-Systems) are supported.

- **Middleware view**: The self-x properties need trust values about a node, and its reliability to host important services.
- **MAS view**: Multi-Agent-Systems calculate trust values about other agents and

abstract from the node they are running on. Therefore their experiences and trust values are about specific agents and normally do not include node information.

To calculate trust the services save so called `RawData` into the TEM. These `RawData` represent the experiences the services had with their interaction partners. These experiences already contain an evaluation of these interactions, i.e., a value between 0 and 1 with 0 representing the worst and 1 the best possible outcome. When a direct trust calculation is initialized, a `Transformer` transforms them into `TransformedData`, e.g., applying a sliding time window. Then an `Interpreter` calculates `TrustData` out of the `TransformedData`. This process is depicted in Figure 5.3.

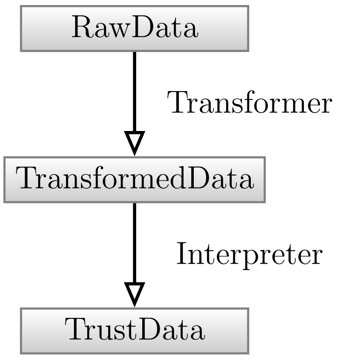


Figure 5.3.: Trust calculation process

RawData represents all experiences gathered with an interaction partner. The type of these experiences are application specific. The Delayed-Ack algorithm, e.g., uses an additional list that contains ACKs of messages that were set to *not received* due to a timeout, which defines a waiting time for ACKs of sent messages. After the timeout has elapsed, a message is considered as lost. These late ACKs need to be verified as ACKs for real messages to prevent manipulation of the reliability value, otherwise a malicious node could send random message numbers as ACKs and those would be considered real without cross checking if those numbers were actually sent. After setting a number to *not received* in the database it is removed from memory to prevent a memory leak. The `RawData` are saved per

- source service, that made the experience,
- target service, with whom the experiences was made,
- target node, which hosted the service the interaction was conducted with,
- facet, and
- context

The ID of a service consists of two parts:

1. The type of the service, usually the fully qualified class name. This default

type can be overridden per `Service` by the `getServiceType` method if required.

2. A universally unique ID based on the java.util.UUID class.

Additionally, services can be set to NULL. In this case the trust value is saved for a node, e.g, in case of the Delayed-Ack algorithm. By saving the trust values in such a fine-grained way, different aggregations of these values can be conducted to provide different trust calculations based on the same data. Some examples are given below (context and facet are considered the same for the examples):

- Calling with a NULL source service, a target service type and a target node, the experiences of all services of the requesting node about all services on the target node that are of that type, whatever specific ID they had, are selected.
- Calling with a source service type, a specific target service and a target node, the experiences off the services of the given type about one specific instance of the target service on the given node are selected.
- Calling with a specific source service, a specific target service and NULL as node, the experiences of that one specific service about the specific target service, independent what node that service ran on, are selected.

Despite being application specific, two abstract methods of the `RawData` interface have to be overridden.

```java
public interface RawData extends Serializable {

  public void addRawData(RawData newRawData);

  public void deleteObsoleteData();
}
```

- **addRawData**: Within this method a new set of `RawData` have to be merged with already existing data. The merge logic itself is application specific, but the method is called by the TEM to add additional `RawData`.
- **deleteObsoleteData**: This method is called each time `RawData` is saved or read from the database, this includes trust calculations. It gives the designer of the `RawData` the chance to delete outdated data to conserve space and to prevent a degeneration of the speed of trust calculations. Many data points can reduce the speed of a trust calculation quite significantly.

TransformedData is a preprocessed version of the `RawData`. For example only some `RawData` can be chosen to be used for the trust caluclation. In addition the format can be adjusted to make the calculation itself simpler.

TrustData is the final calculated trust value. Similar to the aforementioned classes, `TrustData` is application specific as well. To assure compatibility with the reputation metric, each `TrustData` object needs to return its trust value as a single double value, indicated by the method `getTrustValue`, which needs to be overridden by every `TrustData` object. In addition, the `TrustData` object contains the confidence values for that trust value, which can be obtained by the `getConfidence` method.

```
public interface TrustData extends Serializable {

  public String getTargetNodeId();

  public void setTargetNodeId(String targetNodeId);

  public void setTrustContext(String trustContext);

  public String getTrustContext();

  public void setFacet(Facet facet);

  public Facet getFacet();

  public void setTargetServiceTypeOrId(String serviceTypeOrId);

  public String getTargetServiceTypeOrId();

  public ConfidenceValues getConfidence();

  public double getTrustValue();

  public void setSourceServiceTypeOrId(String sourceServiceTypeOrId);

  public String getSourceServiceTypeOrId();
}
```

The other methods in the `TrustData` define the parameters, w.g., which node or services the trust was calculated for. The setter methods are called by the TEM and all set parameters can then be obtained again by the getter methods. In contrast to `RawData`, which is saved for a specific service, the trust value can be about a group of services, hence the *ServiceTypeOrId* methods. This supports the different viewpoints of middleware or MAS systems. The TEM provides a default implementation `SingleValueTrustData`, if a trust value consists of just a single double value.

The following listing shows the methods of the `Trust` interface. The types between angle brackets (< and >) are java specific and define generic types that are checked at compile time.

```
public interface Trust {

    public TrustData calculateDirectTrust(String sourceServiceTypeOrId,
        String targetServiceTypeOrId, String targetNodeId, Facet facet,
        String trustContext, Object... metricParameters)
          throws IncompatibleRawDataException;
    public <R extends RawData, T extends TransformedData,
      U extends TrustData> U calculateDirectTrust(
        String sourceServiceTypeOrId, String targetServiceTypeOrId,
        String targetNodeId, Facet facet, String trustContext,
        Transformer<R, T> transformer, Interpreter<T, U> interpreter,
        ConfidenceMetric confidenceMetric, Object... metricParameters)
          throws IncompatibleRawDataException;

    public void calculateReputation(String sourceServiceTypeOrId,
        String targetServiceTypeOrId, String targetNodeId, Facet facet,
        String trustContext, long timeout,
        ReputationResultListener resultListener);

    public void addRawData(String sourceNodeId, String sourceServiceId,
        String targetNodeId, String targetServiceId, Facet facet,
        String trustContext, RawData rawData)
          throws IncompatibleRawDataException;

    public List<RawData> getRawData(String sourceNodeId,
        String sourceServiceTypeOrId, String targetNodeId,
        String targetServiceTypeOrId, Facet facet, String trustContext);

    public <R extends RawData, T extends TransformedData,
      U extends TrustData> void setTrustMetric(
        String serviceType, Facet facet, String trustContext,
        Transformer<R, T> transformer, Interpreter<T, U> interpreter);

    public <R extends RawData, T extends TransformedData,
      U extends TrustData> void setTrustMetric(
        String serviceType, Facet facet, String trustContext,
        Transformer<R, T> transformer, Interpreter<T, U> interpreter,
        ConfidenceMetric confidenceMetric);

    public Metric<? extends RawData, ? extends TransformedData,
      ? extends TrustData> getTrustMetric(
        String serviceType, Facet facet, String trustContext);
}
```

setTrustMetric: Sets a default metric to use for direct trust calculations. The metric consists of a `Transformer` and an `Interpreter`, where the output type of the `Transformer` needs to match the input type of the `Interpreter`, as well as the confidence metric. The metric is set for the *service type*, *facet* and *context*. The service type is defined by the `getServiceType` method of the `Service` interface. Typically the fully qualified class name of the `Service` class is returned, but more sophisticated types are also possible. By using the service type, every specific instance of a `Service` uses the same `Transformer` and `Interpreter`.

calculateDirectTrust: This method enables the calculation of a direct trust value for the services or the middleware. It comes in two versions: One additionally expects the corresponding `Transformer`and `Interpreter` to use for the calculation, the other tries to take the default ones set by the `setTrustMetric` method. Both methods expect the following arguments:

- **sourceServiceTypeOrId**: This parameter defines, which of the service's data, that made the experiences, should be used for the trust calculation. This can either be a specific instance of a service (e.g., a specific hash service), a service type (e.g. a hash service), or NULL, if the experiences of all services run on his node should be considered.

- **targetServiceTypeOrId**: This defines the service, about whom the trust should be calculated. Either the calculation is about a specific service instance, a service type or, if NULL, about the node itself.
- **targetNodeId**: This specifies the node ID of which the trust is calculated. Either this specifies the node the service or service type is on, or is set to NULL. In this case a trust value of a service aggregated over all the nodes it was on is calculated.
- **facet**: The trust facet to use for the calculation. The RawData have to be saved for this facet. Most of the time, applications use the facet credibility. The Delayed-Ack algorithm uses the facet reliability.
- **context**: The context the trust is calculated in. Most of the time, the context is NULL, since using the service in addition to the node is good enough. The Delayed-Ack algorithm uses a specific context, since his experiences are on node level, hence the services are NULL, and need to be distinguished from the other experiences that might be saved on node level.

Giving less precise or none information on some of the aforementioned parameters results in different aggregation levels for the trust calculation. On the one hand a call with a specific *targetServiceId* and *sourceServiceId* as well as a NULL *nodeId* calculates the trust based on the experience of a specific service, but independent on what node that service was on in its lifetime, which is a typical call in a Multi-Agent-System. On the other hand, a NULL for *targetServiceTypeOrId*, a *targetServiceType* and a specific *nodeId* provides the trust value of a service type on a node based on the experiences of every service on the requester node. Such a request would give an estimation, how appropriate a node was so far for a service type. By providing such a flexible request interface, every system view is supported.

calculateReputation: With this method, a service can obtain reputation data of other services or nodes. The `calculateReputation` method can be called in a similar flexible way as the `calculateDirectTrust` methods. The method sends messages to the node the trust value is requested of, who sends it to all its neighbors, i.e., all nodes that interacted with the target node and therefore are expected to have direct trust information. The TEM applies a `Monitor` to save all nodes that were interacted with by observing outgoing messages and saving the IDs of the target nodes. Then the direct trust value is calculated and returned to the original node. These values are then used as input data for the Neighbor-Trust algorithm described in Section 3.2.

Compared to calculating direct trust, this is an asynchronous method. This means that the method can not wait until all results are returned, because, from the sight of the calling node, the total number of results is not known, as well as the maximal time such a request needs. Therefore the caller of the method has to provide a timeout and an object, an implementation of the `ReputationResultListener` interface, that can receive the result of the reputation calculation after the timeout has elapsed.

```
public interface ReputationResultListener {
  public void calculatedReputation
    (SingleValueTrustData reputationData);
}
```

Figure 5.4 depicts the message flow of the method.

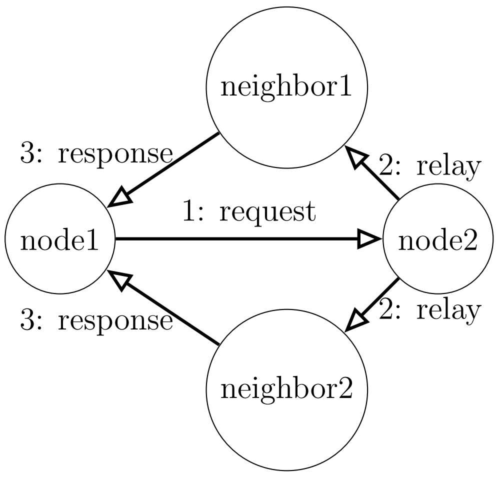


Figure 5.4.: Message flow on a reputation request

addRawData: Adds new `RawData` to the TEM. The data is saved to the identifiers *sourceService*, *targetService*, *targetNode*, *facet* and *context*. If some `RawData` object already exists for these identifiers, the `addRawData` method is called with the new object and both experiences are merged. The merged object is then saved.

getRawData: Returns the `RawData` object for the identifiers described above.

An overview of the classes and interfaces used for trust calculations in the TEM, also called the **trust metric infrastructure** (TMI), can be seen in Figure 5.5

5.4. Confidence

Another big part of the TMI is the `ConfidenceMetric` interface, with the default implementation `ConfidenceMetricImpl` that realizes the metrics described in Section 3.3. Every `Interpreter` is given the `ConfidenceMetric` in its `interpret` method, besides the `TransformedData`. This is the same class given in the `setTrustMetric` method. This enables the `Interpreter` to calculate the confidence and set it in the calculated `TrustValue`.

```java
public interface ConfidenceMetric {

  public abstract ConfidenceValues calculateConfidence(
    List<RatedExperience> experiences);

  public abstract ConfidenceValues calculateConfidence(
    List<RatedExperience> experiences, List<Double> weights);

  public abstract double calculateTotalConfidence(double numberConfidence,
    double ageConfidence, double varianceConfidence);

  public abstract double calculateNumberConfidence(
    List<RatedExperience> experiences);

  public abstract double calculateAgeConfidence(
    List<RatedExperience> experiences);

  public abstract double calculateVarianceConfidence(
    List<RatedExperience> experiences);

  public abstract double calculateVarianceConfidence(
    List<RatedExperience> experiences, List<Double> weights);

  public boolean isConfidenceValuesOutdated(ConfidenceValues
    confidenceValues);
}
```

The `ConfidenceMetricImpl` class contains all confidence parameters as fields, which are set to default values by the TEM. If another set of parameters has to be used, the `ConfidenceMetricImpl` class can be instantiated with these parameters and that class then used when calculating trust. To use the individual confidence metric, it can either be set in the `setTrustMetric` method or given in the `calculateDirectTrust` method of the `Trust` interface. To make the confidence metric compatible with every kind of experience, another interface, the `RatedExperience` is introduced.

```java
public interface RatedExperience extends Serializable {

  public abstract long getTimestamp();

  public abstract double getRating();
}
```

The interface needs to be implemented either by all experiences saved in `RawData` or generated by the `Transformer`. It tells the confidence metric, when the experience happened (`getTimestamp`) and rates each experience with a number between 0 and 1 (`getRating`). This information is sufficient for the confidence calculation and abstracts the actual raw data that was used to calculate the trust value, making it useable for any kind of data.

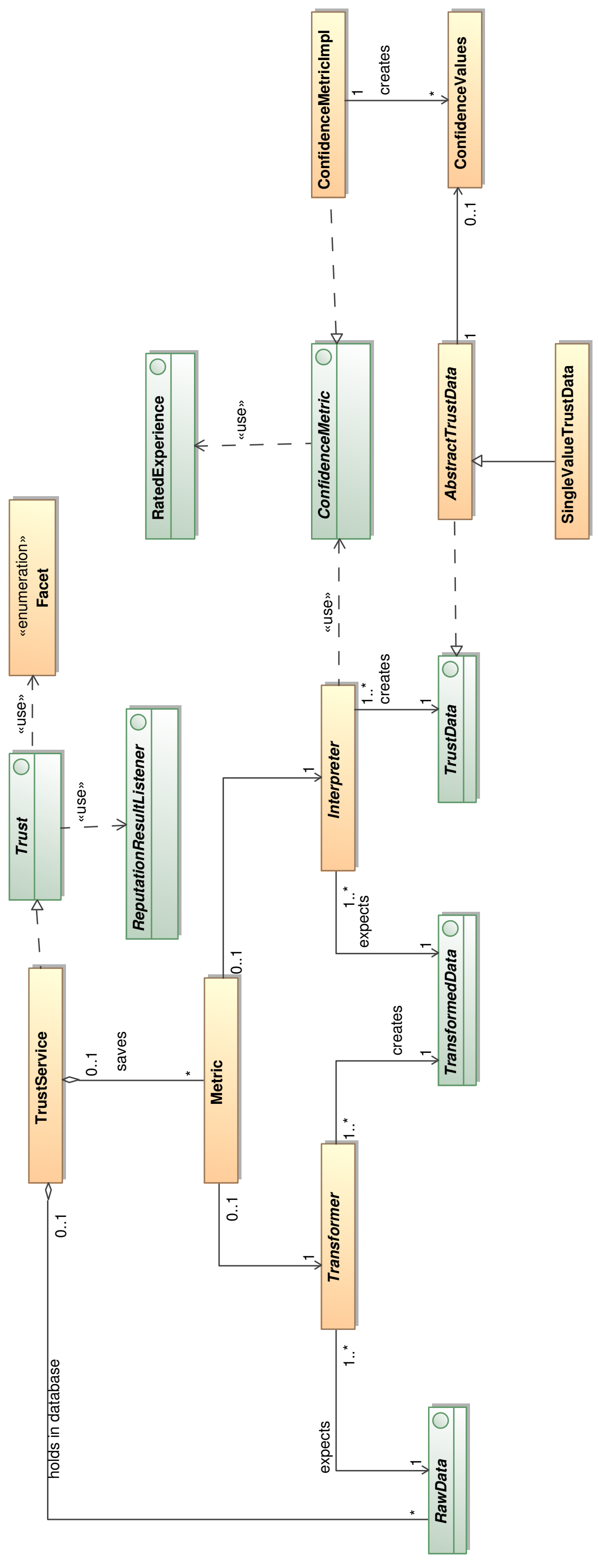


Figure 5.5.: Reduced class diagram of the trust metric infrastructure

6. Conclusion

In this work a framework to calculate trust in Organic Computing Systems was introduced. The framework consists of metrics to calculate direct trust, confidence, reputation, as well as a metric to combine these three parts. In this thesis, trust encompasses several facets, e.g., reliability and credibility, and can be applied to different contexts. Therefore, most trust metrics were designed to support several kinds of systems, e.g, a computing grid or energy grid. The direct trust metric Delayed-Ack gathers reliability information of other nodes on middleware level, while the other parts, i.e., confidence, reputation, and the aggregation of all, work for all trust facets, as long as a direct trust metric is supplied. However, the metrics were mainly designed to improve the self-x properties of Organic Computing Systems. In particular, this means that trust was applied to a pure computational system without human participants.

In addition to the trust framework, the Trust-Enabling Middleware (TEM) was designed, which allows services, that are hosted on nodes running the middleware, to exploit the presented trust metrics. Services can also add their own trust metrics for direct trust through a well defined interface. The TEM was developed in Java to be platform independent, allowing it to even run on mobile devices supporting Java like Android smartphones. The trust metrics, especially the Delayed-Ack algorithm to asses the reliability of other nodes, are fully implemented. Together with the monitoring system to observe the message flow and to add piggy-back information on application messages, the TEM is ready to host trust-enhanced self-x algorithms.

Additionally, the importance of each part of the trust framework, i.e., direct trust, confidence, and reputation has been evaluated, to gain the most benefit of a system. For this, Automated Design Space Exploration (ADSE) with the help of a particle swarm algorithm was applied. The use of ADSE was required due to the dimension of the design space of $\approx 3.36 * 10^{32}$ possible parameter settings. The most important aspect of the evaluation was the change in behavior of the participants, when the benefit from interacting with a participant changes for the worse and the system has to adapt. Beside the impact of each trust metric, the turning point when switching from reputation to direct trust when making the decision with whom to interact, was investigated. If there is a specific point, when to change from reputation to direct trust. Or if there is a gray zone, where both parts are important but the weight shifts slowly towards direct trust.

In experiments, one characteristic stood out: One parameter, the history length, dominated the other twelve. The history length defines the amount of past experiences, which are considered when calculating the trust values, be it direct trust or reputation. Intuitively, one would expect to consider several experiences to get a good assessment of someones' behavior, yet a history length of two proved to be the best choice. By using only the last two experiences, the system can adjust much faster to changing behavior, while still maintaining a good enough estimation of the targets' current behavior. With the DTC metric, the influence of the other parameters was the strongest, reputation (DTCR metric) mitigated most of the variance. This behavior could be observed in nearly all scenarios, the DTC (direct trust and confidence) metric with only two behavior changes being the only exception, where the other parameters where more important than the history length. An explanation for this might be, that in a highly stable system, where all participants stay true to their behavior nearly all of the time, the interaction partners rarely need to adapt. Adding reputation reinstated the dominance of the history length again, though. And even with only eight behavior changes, the history length is again dominant in all scenarios.

This leads to the conclusion, that exploiting the stable state of a system weights less than a fast adaption to change. The opposite is only true if the time between changes, i.e., the time of stability, is sufficiently long. So in a system showing high behavior fluctuation, fast adaption is most important. A history length of two seems to be sufficient for computational systems. In comparison, humans feel subjectively better if they can resort to a larger amount of past experiences, regardless if that many experiences are rationally required to asses the trustworthiness of an interaction partner.

Another prevalent effect in each scenario was a higher achieved cumulative benefit when experience ratings were based on binary instead of continuous values, i.e., only 0 (bad experience) or 1 (good experience) compared to values between 0 and 1. Intuitively, this seems unexpected, since a continuous rating allows for a more precise estimation. But combined with a preferable low history length, there are only three possible trust values based on binary experience ratings: 0, 0.5, and 1. A trust value of 0 or 1 is based on identical experiences (all 0 or all 1) and a strong indication that the next experience will be the same, especially if the actual behavior of the interaction partner is close to the extremes of 0 and 1. Since the goal of the interactions is to make as many good experiences as possible, i.e., experiences rated with 1, a streak of good experiences provides a good estimation about the future. At the same time, a short history length, in this case two, gives the opportunity to adapt fast to a behavior change; see above.

It seems that a binary basis for experience ratings is preferable to continuous ratings. However, the rating function depends on the underlying application. The Delayed-Ack algorithm is suitable to be binary rated (0 for a lost message, 1 for a received message). Other applications can only sensibly use continuous ratings, e.g., the energy grid application. Here, the experience rating represents the divergence between a power prediction and the actual power production of a power plant. This divergence requires a continuous scale by nature.

Regarding the turning point between direct trust and reputation, the evaluations have shown that a single point between these two can not be defined. Essentially the opposite was the case. Reputation was still considered with high confidence, as well as direct trust with low confidence. This means that both reputation and direct trust are considered when assessing the trustworthiness of an interaction partner, with a steady shift from reputation to direct trust when the confidence in one's own experiences increases. This is similar to how humans utilize trust. Preferences differ from person to person, and there are extremes on both ends; but humans are still influenced by the recommendations of others although they had their own experiences so far. This shows that computer systems can profit from the inclusion of trust like humans.

A next step to research are the effects of a low history length. If the observed effect carries over to other scenarios, or if a transfer to user trust is possible. An answer to these questions could increase the insight of the trust concept. Within the field of Organic Computing, the presented trust metrics are now ready to be integrated into the self-x properties, including self-configuration, self-optimization, and self-healing. The consideration of trust allows a differentiation of service importance, moving more important services to more reliable nodes and, therefore, increasing the robustness of the system. A degeneration of reliability of a node over time enables the self-configuration to predict an impending node failure, which allows the application of preemptive measures, e.g., moving services from an endangered node, before it actually crashes.

Another important aspect is the robustness of the trust metrics themselves. When integrated into the self-x properties, the robustness of the trust metrics is most important and a manipulation by an attack can jeopardize the stability of the system. Marmól and Peréz [39] describe attacks on trust metrics and an evaluation of the metrics against these attacks would be a logical next step.

A. Proof to calculate maximal variance

Be μ the weighted arithmetic mean with $\mu = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}$, where x_i is the value at time i and w_i the weight for value x_i at time i.

Based on [16] the formula for weighted variance comes to:

$$\sigma^2_{weighted} = \frac{1}{\sum_{i=1}^{n} w_i}(\sum_{i=1}^{n} w_i(x_i - \mu)^2)$$

Assumption: In case of $0 \leq \mu \leq 1$ the variance is maximal if all values $x_i \in \{0, 1\}$, i.e., the mean is based solely on 0 or 1 values.

Proof:

Be $w_c = \sum_{i=1}^{n} w_i$, x_1 variable and $x_2 \ldots x_n$ be constant.

$$\begin{aligned}
f(x_1) &= \frac{1}{w_c}(\sum_{i=1}^{n} w_i(x_i - \frac{1}{w_c}\sum_{j=1}^{n} w_j x_j)^2) \\
&= \frac{1}{w_c}(w_1(x_1 - \frac{1}{w_c}\sum_{j=1}^{n} w_j x_j)^2 + \sum_{i=2}^{n} w_i(x_i - \frac{1}{w_c}\sum_{j=1}^{n} w_j x_j)^2) \\
&= \frac{1}{w_c}(w_1(x_1 - \frac{1}{w_c}w_1 x_1 + \underbrace{\frac{1}{w_c}\sum_{j=2}^{n} w_j x_j}_{c_1})^2) \\
&+ \frac{1}{w_c}\sum_{i=2}^{n} w_i(-\frac{1}{w_c}w_1 x_1 + \underbrace{x_i - \frac{1}{w_c}\sum_{j=2}^{n} w_j x_j}_{c_2(i)})^2 \\
&= \frac{1}{w_c}w_1(\frac{w_c - w_1}{w_c}x_1 + c_1)^2 + \frac{1}{w_c}\sum_{i=2}^{n} w_i(-\frac{1}{w_c}w_1 x_1 + c_2(i))^2
\end{aligned}$$

1. Deviation:

$$\begin{aligned}
f'(x_1) &= \frac{1}{w_c} w_1 2(\frac{w_c - w_1}{w_c} x_1 + c_1)\frac{w_c - w_1}{w_c} \\
&+ \frac{1}{w_c}\sum_{i=2}^{n} w_i 2(-\frac{1}{w_c} w_1 x_1 + c_2(i))(-\frac{1}{w_c} w_1) \\
&= \frac{1}{w_c} w_1 2 \frac{(w_c - w_1)^2}{w_c^2} x_1 + \underbrace{\frac{1}{w_c} w_1 2 \frac{w_c - w_1}{w_c} c_1}_{c_3} \\
&+ \frac{1}{w_c}\sum_{i=2}^{n} w_i 2(-\frac{w_1}{w_c})^2 x_1 + w_i 2(-\frac{w_1}{w_c}) c_2(i) \\
&= \frac{2w_1(w_c - w_1)^2}{w_c^3} x_1 + c_3 + \frac{1}{w_c}(w_c - w_1) 2 \frac{w_1^2}{w_c^2} x_1 + \underbrace{\frac{1}{w_c}\sum_{i=2}^{n} w_i 2(-\frac{w_1}{w_c}) c_2(i)}_{c_4} \\
&= \frac{2w_1(w_c - w_1)^2}{w_c^3} x_1 + \frac{2w_1^2(w_c - w_1)}{w_c^3} x_1 + \underbrace{c_3 + c_4}_{c_5} \\
&= \frac{2w_1(w_c - w_1)((w_c - w_1) + w_1)}{w_c^3} x_1 + c_5 \\
&= \frac{2w_1(w_c - w_1)}{w_c^2} x_1 + c_5
\end{aligned}$$

2. Deviation:

$$f''(x_1) = \frac{2w_1}{w_c^2}(w_c - w_1)$$

The 2nd deviation is > 0 for $n > 1$ and weights > 0. In case of $n = 1$ the sum of all weights w_c consists of only the first weight w_1, therefore $w_c = w_1$, which results in 0 for the second deviation. The same is true for weights equal to 0. Otherwise the second deviation is always greater 0, regardless of the values of x_i, resulting in an increasing gradient of the original function. The maximum of the function is therefore at the limits of the domain, in this case 0 or 1. Without loss of generality this conclusion applies to all x_i. Therefore the variance with all $x_i \in \{0, 1\}$ is maximal.

If all $x_i \in \{0, 1\}$ the weighted mean algorithm can be written as:

$$\begin{aligned}
\mu_{maxv} &= \frac{\sum_{\{i\in X|x_i=1\}} w_i x_i + \sum_{\{i\in X|x_i=0\}} w_i x_i}{\sum_{i=1}^{n} w_i} = \frac{\sum_{\{i\in X|x_i=1\}} w_i}{\sum_{i=1}^{n} w_i} \\
\implies \mu_{maxv} \sum_{i=1}^{n} w_i &= \sum_{\{i\in X|x_i=1\}} w_i
\end{aligned}$$

Also:

$$\sum_{\{i\in X|x_i=0\}} w_i = \sum_{i=1}^{n} w_i - \sum_{\{i\in X|x_i=1\}} w_i$$

The weighted confidence formula has a similar special case for $x_i \in \{0,1\}$:

$$\begin{aligned}
\sigma^2 &= \frac{1}{\sum_{i=1}^{n} w_i}\left(\sum_{\{i\in X|x_i=1\}} w_i(1-\mu)^2 + \sum_{\{i\in X|x_i=0\}} w_i(0-\mu)^2\right) \\
&= \frac{1}{\sum_{i=1}^{n} w_i}\left(\mu\sum_{i=1}^{n} w_i(1-\mu)^2 + \left(\sum_{i=1}^{n} w_i - \mu\sum_{i=1}^{n} w_i\right)(0-\mu)^2\right) \\
&= \mu(1-\mu)^2 + (1-\mu)(0-\mu)^2 \\
&= \mu(1-2\mu+\mu^2) + (1-\mu)\mu^2 \\
&= \mu - 2\mu^2 + \mu^3 + \mu^2 - \mu^3 \\
&= \mu - \mu^2
\end{aligned}$$

In total the formula for the maximal variance is, with or without weights:

$$\sigma^2 = \mu - \mu^2$$

When all weights are set to 1, the weighted variance is equivalent to the normal variance, therefore this formula holds true for normal variance as well.

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