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Coordination of Just-in-Time Deliveries with Multi-attribute Auctions

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Abstract. Just-in-time deliveries are crucial for many industries. They are particularly essential when the properties of the delivered resource or the demanding processes are sensitive in time. Rigid, centralized planning tends to fail, especially in dynamic environments with distributed decisions and control. Under the constraints of distributed decisions and control, auctions promise an efficient allocation of resources. However, a dedicated design of auctions for just-in-time deliveries, which can be incorporated into the design of an IT artifact, is still lacking. We contribute a linear and a quadratic multi-attribute scoring rule for an automated execution by software. We evaluate the artifact in a simulation experiment and reveal the effects of the scoring rules for just-in-time deliveries. Our results provide evidence that the artifact effectively coordinates just-in-time deliveries, which also holds when considering one additional side constraint.

Keywords: Just-in-Time Delivery, Multi-attribute Auction, Scoring Rule, Distributed Decisions and Control

1 Introduction

Just-in-time (JiT) deliveries are demanded by many industries [9, 13]. In general, JiT deliveries are encouraged by the reduction of stocks so as to save storage costs and place, to release tied capital, and to diminish the risk of sunken costs [10, 16, 22]. The risk of sunken costs exists in particular for resources with perishable properties. The road pavement process illustrates the JiT requirements: As soon as the paver's asphalt reservoir runs low it has to be provided with asphalt in the right temperature for further processing. The paver must not wait, because discontinuances during the processing lead to irregularities in the pavement. As a result of poor paving, the stability of the road is affected negatively, which then causes high costs for maintenance and repair and impairs the driving safety [5].

When just-in-time deliveries are critical in environments where prospects are hardly possible, it is advisable to establish short-cyclic demands, so that an adjustment to unforeseen circumstances is possible. The use of IT enhances the adaptability to environmental dynamics and the availability of IT permeates throughout all industries. Yet, many production processes are constituted as a supply chain with distributed decisions and control. An integrated conceptualization would fail, because there is no

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effective way to impose directives hierarchically. This situation is prevalent in the nature of many supply chains.

The construction industry sets a good example. During the production process, numerous providers are involved, and each of them complies with her own objectives. Supply chain management and the maintenance of just-in-time deliveries is a tremendous issue [17, 18]. Anyhow, the construction machines are increasingly equipped with digital sensor technology, as well as with digital information processing technology. Coordination relevant data is or becomes available and usable. The problem is, indeed, the distribution of decisions and control.

To address this situation we draw from the Mechanism Design Theory (MDT) and provide an auction as coordination artifact. Auctions are determined by an explicit set of rules [14], and hence their concepts are suitable for adoption by IT engineers. The primary outcome of an auction is classically an allocation. However, we utilize auctions also as a mechanism to find the best agreement for certain characteristics of a delivery order among multiple providers. The characteristics are reflected by the general objectives of JiT deliveries, and encompass the dimensions (1) *prize*, (2) *quantity*, (3) *condition* (quality), (4) delivery *time*, and (5) *place* of delivery. We incorporate the dimensions as attributes for an auction, and design a linear and a quadratic multi-attribute scoring rule to determine the provider who is awarded a delivery order. The linear scoring rule scores proportionally to what extent the JiT objectives are accomplished. The quadratic scoring rule allows for a more sophisticated scoring, since the marginal scoring is not constant. By providing and evaluating our multi-attribute auction, we contribute a method for the coordination of JiT deliveries.

The auction as coordination method allows for an efficient allocation of delivery orders to the best-suited deliverer. The deliverer might also be detected from one or several contractual partners' fleet of transport vehicles. An advantage of this procedure, in comparison to a fixed schedule, is that the order retrievals can be adjusted individually to the currently present circumstances. On a road construction site, for example, when there is an interruption in the paving process, one can observe the situation where the asphalt delivering trucks back up at the paver. As a consequence the unnecessarily waiting trucks are later on lacking for the provision of supplies.

We pose the following research question: *What is the effect of using multi-attribute auctions for just-in-time deliveries?* From an IS perspective, we investigate the effect of our IT artifact on the organization of a supply chain. To answer this question, we report the results of a simulation of the artifact. We reveal the implications of the respectively implemented scoring rules for the coordination of just-in-time deliveries, and compare both scoring rules.

Relevance of our research is indicated by the example from above, but also given due to the research gap in this field of IS research. Multi-attribute auctions have already been realized for computer-aided task- and service-allocation [8, 11, 12, 20]. Still, a design of auctions for JiT deliveries is lacking.

The paper is structured in the following way: Sec. 2 provides an overview of the state of the art. In sec. 3 our scoring rules are developed as a coordination artifact. Sec. 4 reports the evaluation of our artifact. We close our paper with a conclusion and an outlook in sec. 5.

2 State of the Art

The paper at hand relates to other approaches which aim at inducing JiT performances through auctions. Witzel & Endriss [21] augment multi-unit auctions with up to four time constraints. The formulation of narrow time restrictions enables auctions for just-in-time deliveries. However, the approach is driven by a logic calculus and thus the assessment of the time constraints is either 'true' or 'false'. Soft winner determination for the case that no bidder fits the time restrictions is not possible, and so is the determination of ordering relations not possible either.

Another approach is presented by Nunes et al. [15]. They consider task allocation with time-sensitive single-item sequential auctions for spatially distributed robots. Therefore, each task is assigned an earliest start time, a latest finish time, and an estimated processing time. An appropriate small choice of the time windows addresses JiT requirements. However, integrative multi-attribute auctions are not addressed.

An early model for multi-attribute auctions has been inquired by Che [7]. Che has involved two attributes, one for the prize *p*, and one for the quality *q*. The utility for a bidding agent $b \in A_B$ in dependence of these two attributes is determined by $u(b,(p,q)) = V(q) - p$, where *V(q)* is the valuation of the given quality value. In particular, *V* must be differentiated with respect to just-in-time deliveries.

Our paper is also related to work about allocation of computational jobs in service networks, as multi-attribute auctions are used. Dinther et al. [8] incorporate automated negotiations with a scoring rule for services. The scoring rule is of the form $S(\nu) = \sum_i \lambda_i \|\nu_i\|$, where ν is a configuration of a complex service. The service is composed in a service network and the index *i* indicates a node which provides a service. Dinther et al. provide results for the formation of service networks. However, the problem at hand, pertaining to just-in-time deliveries, is to find one sole agent who is best suited for the fulfillment of a demand.

Multi-attribute auctions have also been used to improve sustainability in cloud computing. Widmer et al. [20] factor in the expected energy consumption for the allocation of services in cloud computing. In their simulative evaluation, Widmer et al. assigned different weights to the prize of a service and its energy consumption. They finally assessed the utility ratio of the outcome. However, the scoring model directly incorporates energy specific key figures, and thus a transfer onto the inducement of just-in-time deliveries is not given.

In an experimental setting, Haak & Gimpel [11] have investigated bidding rules for the automation of negotiations for service level agreements (SLA). They compared three rules for multi-attribute auctions, among others with respect to individual rationality and incentive compatibility. The rules are: (1) Tuple-bidding, where the customer proposes a tuple of price and quality and the seller accepts or declines. (2) Scoring-bidding, where the customer gives a scoring function and the seller sets a quality and a prize accordingly or declines. (3) Discount-bidding, which is the same as (2) but allows for discounts. The auction rules only compare prize with quality directly. It is not specified how different quality attributes interact with each other and how the interplay influences the overall outcome.

Another approach for the automation of the negotiation for SLA by multi-attribute auctions is given by Kieninger et al. [12]. They consider a multi-attribute offer as a tuple of service incident patterns, such as outages or disfunctions. The winner of the auction is determined by the expected business costs, which are computed by multiplying the frequencies of the service incident patterns with the business costs for a service. However, the last two presented papers do not fit to the problem of inducing just-in-time deliveries.

Our paper is also related to work of Bichler et al. [4], who give a comprehensive overview of the usage of auctions for procurement with IT. In an earlier work, Bichler [1] has investigated the more general question, whether multi-attribute auctions achieve better outcomes than traditional auctions for the prize of an item only. Later, Bichler & Kalagnanam [2] have applied the concept of multi-attribute auctions to configurable offers and to auctions with multiple sources. Although progress has been made, regarding multi-attribute auctions with IT, the design of scoring rules for the automated procurement of just-in-time deliveries has not been inquired, yet.

Quadratic scoring rules were not implemented in any of the preceding works.

3 Artifact Design

3.1 Formal Framework

We take an auction as a mechanism for resource allocation between one auctioneer and multiple bidders, which is constituted by a bidding process over potentially several attributes of one or more items [3]. The items are the resources that shall be allocated, and the attributes determine the characteristics of what an agreement must be found − besides the pure allocation of the item. The notion of a resource, i.e. of the items, is to be understood in a broad sense that covers tangible goods, as well as intangible goods, or services, so objects, as well as performances, or even commitments to eventually execute a task. The objective of the auction is to optimize the agreement for the attributes from the auctioneer's viewpoint, respectively to find the bidder with whom the best agreement can be found.

We employ the following basic model: I is the set of items, and $B \subseteq \wp(I)$ is the set of item bundles from the power set over I. C is the set of attributes (characteristics), where $Y_c \subseteq \mathbb{R}$ is the value range of $c \in C$. Each bundle is attributed with an array of characteristics to which we refer with $\boldsymbol{\mu} \subseteq B \times C^M$. Because the relation $\boldsymbol{\mu}$ is functional, we obtain the attributes of a bundle $b \in B$ by $\boldsymbol{\mu}(b)$. For the sake of notation, please be aware that for each bundle, M may be a different dimension reflecting the number of attributes. Each attribute is assigned a respective value by $\boldsymbol{\nu} : \boldsymbol{\mu} \to Y^M$, where $Y = \bigcup_{c \in C} Y_c$.

A is the set of agents, the set of bidders is $A_B \subseteq A$, and the set of auctioneers is $A_A \subseteq A$. Each agent $a \in A$ gets the utility $u(a, \boldsymbol{\nu})$. Note, that $\boldsymbol{\nu}$ is in fact a triple $B \times C^M \times Y^M$, which means that not only the attributes and its values are essential, regarding the utility for an agent, but the bundle itself, too. Let us exemplify the formality (later we will simplify the notation).

Example 1: The item set

$$I = \{Asphalt, Concrete\}$$

consists of a transport order for asphalt and for concrete. There are only two bundles, comprised of one item each, i.e.

$$B = \{\{Asphalt\}, \{Concrete\}\}.$$

Both bundles have the same attributes,

$$\mu(\{Asphalt\}) = \mu(\{Concrete\}) = (Time, Prize),$$

being the delivery time and the charged prize. The attribute values shall be equal, e.g.

$$\nu(\mu(\{Asphalt\})) = \nu(\mu(\{Concrete\})) = (30.0, 70.0),$$

where the units of the first and the second component are “minutes” and “Euro per ton”, respectively. It is obvious that for an asphalt paving agent the utility for the asphalt delivery should be higher than the utility for the concrete delivery, although the attributes and its values are exactly the same.

Example 2: Now let us consider the item set consisting of orders for diverse asphalt types that are needed for a road’s base layer, binder layer and wearing layer respectively,

$$I = \{Base, Binder, Wearing\}.$$

They can be purchased individually or together, so the bundle set

$$B = \{\{Base\}, \{Binder\}, \{Wearing\}, \{Base, Binder, Wearing\}\}.$$

The single item bundles have all the same attributes,

$$\mu(\{Base\}) = \mu(\{Binder\}) = \mu(\{Wearing\}) = (Time, Prize).$$

The combined bundle has the attributes

$$\mu(\{Base, Binder, Wearing\}) = (Time_1, Time_2, Time_3, Prize),$$

where the semantic of the $Time_i$-values is the delivery time of one particular kind of asphalt. In a similar way subsequently delivered batch orders could be represented, e.g. with the item set

$$I = \{Base_1, Base_2, Base_3\}.$$

Based on the notion above and on prior literature [6], we qualify the core properties of auctions by three criterions: (1) Number of items, (2) attribute set, and (3) character.

(1) The number of items to be auctioned has a significant impact on the complexity of the winner determination problem. We only distinguish if single items are auc-

tioned separately, or whether bids over bundles of items are possible. In the former case $B \equiv I$, by which we mean that B contains exactly the same amount of elements as I and each element of B contains exactly one element of I. The latter case is referred to as combinatorial auction, where the number of possible bundles, and hence the search space for an optimal bid, may be exponential in the number of items. (2) The attribute set states whether the auction consists of a single attribute or of multiple attributes, i.e. whether $M = 1$. The former case corresponds to the idea of perfect competition for a prize only. The interesting aspect in the latter case is to enable efficient outcomes with respect to the auctioneer's and bidders' prioritization of the attributes, which potentially allows for tradeoffs. (3) Therefore, we address also the character of an auction, which can either be integrative or distributive. In distributive auctions either the auctioneer wins and the bidders lose per bid or vice versa [19]. Integrative auctions offer the opportunity to find compromises between the auctioneer and a bidder, which are not bound to the fixed pie assumption of distributive auctions, i.e. win-win outcomes are possible. More formally, let ν'' and ν' be two distinct value characteristics of a bid for a bundle b and $a_1, a_2 \in A$ be two distinct agents. An auction is integrative if $u(a_1, \nu'') > u(a_1,\nu') \wedge u(a_2, \nu'') > u(a_2,\nu')$ is possible.

Based on that conceptualization our contribution is a single-item, multi-attribute, integrative auction.

3.2 The Auction Model

The essential part for the design of the auction is the triple ν. This variable aggregates an item bundle with its attributes and the respective attribute values. Since the auction shall coordinate just-in-time deliveries, the item set contains an order for the delivery of a resource, $I = \{Delivery\ order\}$. The bundle set contains only the one item, $B = \{\{Delivery\ order\}\}$. The *Delivery order* here is rather a placeholder for an order to deliver a particular resource, e.g. asphalt. Because there is solely one element in the bundle set, we omit the explicit statement of the arguments for μ and ν. It is unambiguous to what we refer respectively. Although we regard technically a single-item auction we always refer to "the bundle" to retain stringency. The restriction to a single item reduces complexity, but in principle our model allows for combinatorial auctions, too.

The attribute set $C = \{Prize, Quantity, Condition, Time, Place\}$. The attributes of the bundle $\mu = (Prize, Quantity, Condition, Time, Place)$. We use in the following the respective first two letters as abbreviation, i.e. *Pr, Qu, Co, Ti, Pl*. The value range of each attribute $c \in C$ is given by Y_c. We require that each $Y_c \subseteq \mathbb{R}$, so each attribute must be mapped to a real number. The satisfaction of this requirement is not straightforward regarding the attributes *Condition* and *Place*. A place is usually given by a Cartesian product of two or three real numbers specifying coordinates. However, there is always a natural possibility to express the distance to a reference point with one sole real number. One can consider the shortest path in a road network to the reference point, or the time that is needed to get there, or even the consumption of fuel. No matter which projection is used, information will be lost. Still, for our purpose the one-dimensional distance to a reference point is sufficient. The reference point is the aspired place of delivery. Bidders can bid for the distance to that reference point as delivery place. In cases where the place is not subject for negotiation the only accepted distance is zero.

The attribute describing the condition poses more difficulties. First of all it is not always straightforward to assess the condition of a resource quantitatively. That is why we introduce formally an auxiliary function that we call y_{Co} and that returns a real number as value for the *Condition* attribute. In the best case, y_{Co} is a sensor which returns a measurement directly, e.g. a temperature or a viscosity. The function may however also be a mapping from qualitative attributes onto a real number. The latter case is not straightforward, though.

The auction is carried out by an agent $a \in A_A$ who demands a resource at a specific time. To find the bidder who is best suited for the fulfillment of the demand, the auctioneer agent a scores the bids with a scoring function $S : \boldsymbol{\nu} \rightarrow \mathbb{R}$. Based on the scoring function S the order is awarded to the bidder $b^* \in A_B$ who attains the highest score. Please note that the scoring of a bid is not necessarily identical to the utility from that bid. We take the scoring function as a technical means to map priorities on the auction attributes. Since the co-domain of the scoring function S is $\mathbb{R}$, the array of attribute values $\boldsymbol{\nu}$ must be mapped onto one sole number. A reduction of multiple values to one value is non-trivial because information is lost inevitably. Our general approach is to score each attribute value ν_c individually, and to connect the individual scores $S_c(\nu_c)$ with a commutative, associative operator "$\circ$".

$$S(\boldsymbol{\nu}) = S_{Pr}(\nu_{Pr}) \circ S_{Qu}(\nu_{Qu}) \circ S_{Co}(\nu_{Co}) \circ S_{Ti}(\nu_{Ti}) \circ S_{Pl}(\nu_{Pl}).$$

Commutativity and associativity make sure that the order, in which the individual scoring functions are computed, is irrelevant. We use the simple additive operation:

$$S(\boldsymbol{\nu}) = S_{Pr}(\nu_{Pr}) + S_{Qu}(\nu_{Qu}) + S_{Co}(\nu_{Co}) + S_{Ti}(\nu_{Ti}) + S_{Pl}(\nu_{Pl}) = \sum_{c \in C} S_c(\nu_c).$$

With the additive operation the score of each attribute is considered independently. Hence, one particularly favorable attribute value can potentially compensate for an attribute with a low score. When used, for instance, the multiplication, then the entire scoring $S(\boldsymbol{\nu})$ converged to zero as soon as the score of one single attribute value becomes close to zero. Consecutively, the scoring functions need to be designed.

3.3 The Scoring Rules

Basically, the linear scoring rule scores the deviation of an attribute value from the aspired value ν_c^{opt} for the corresponding attribute c. The minimum and maximum attribute values are defined by ν_c^{min} and ν_c^{max}. It is $\nu_c^{min} \leq \nu_c^{opt} \leq \nu_c^{max}$ and the value range $Y_c = [\nu_c^{min}, \nu_c^{max}]$. Note, that the value range of the attributes is the domain of the scoring function. The weighting factor λ_c constitutes at the same time the maximum score for the attribute c. The *linear* scoring rule for the individual attributes c reads:

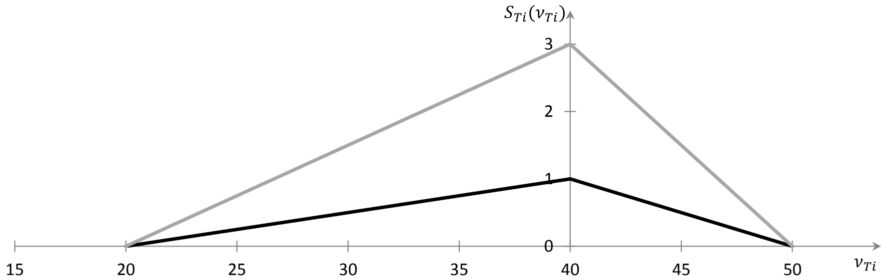

Fig. 1. Linear scoring function with different weighting factors (for the *Time* attribute)

$$S_c(v_c) = \begin{cases} \lambda_c \cdot \dfrac{v_c - v_c^{min}}{v_c^{opt} - v_c^{min}} & , v_c^{min} \le v_c < v_c^{opt} \\ \lambda_c \cdot \dfrac{v_c - v_c^{max}}{v_c^{opt} - v_c^{max}} & , v_c^{opt} < v_c \le v_c^{max} \\ \lambda_c & , v_c = v_c^{opt} \\ \perp & , \text{otherwise} \end{cases}$$

For the score at the interval boundaries it always holds $v_c^{min} = v_c^{max} = 0$. The maximum score is only realized for the aspired attribute value $S_c(v_c^{opt}) = \lambda_c$. The explicit definition of the case for $v_c = v_c^{opt}$ allows to set $v_c^{min} = v_c^{opt}$, or $v_c^{opt} = v_c^{max}$, or $v_c^{min} = v_c^{opt} = v_c^{max}$. Fig. 1 depicts the function graph of two instances of the linear scoring rule for the attribute *c* = *Time*. Both graphs are underlay with $v_{Ti}^{min} = 20$, $v_{Ti}^{opt} = 40$, and $v_{Ti}^{max} = 50$, but the black graph is underlay with the weighting factor $\lambda_{Ti} = 1$ and the gray graph is underlay with the weighting factor $\lambda_{Ti} = 3$. A deviation from the aspired attribute value is penalized linearly. If $S_c(v_c) = \perp$ then the value of the attribute *c* is out of the settlement range. The settlement range is described by Walton & McKersie [19] and we adopted the concept in the following way: An agreement for the bundle can only be settled if $\forall\ c \in C : v_c \in Y_c$. That means, if bidders make an offer where at least one attribute value is beyond the auctioneer's acceptable value range, then there is no agreement for the bundle at all.

The linear scoring rule cannot express that the marginal scores may be dependent of the current score of the respective attribute value. A deviation around the optimal attribute value shall potentially have a smaller effect than the same deviation at the interval boundaries. A nearby enhancement of linear models is the extension to a second-degree polynomial. Therefore, we posit the following (mathematical) conditions:

$$
\begin{array}{llllllll}
(1) & S_c(v_c^{min/max}) & = & a\cdot(v_c^{min/max})^2 & + & b\cdot v_c^{min/max} & + & c \overset{!}{=} 0 \\
(2) & S_c(v_c^{opt}) & = & a\cdot(v_c^{opt})^2 & + & b\cdot v_c^{opt} & + & c \overset{!}{=} \lambda_c \\
(3) & \dfrac{d}{d v_c} S_c(v_c^{opt}) & = & a\cdot 2v_c^{opt} & + & b & & \overset{!}{=} 0
\end{array}
$$

In expression (1) either v_c^{min} or v_c^{max} is applied, according to whether the left-hand or the right-hand interval is determined. The expression ensures that the score at the interval boundaries is zero. Expression (2) ensures that the aspired attribute value gets the maximum score. In difference to the linear model, there is a third degree of freedom. With expression (3) we define that the marginal score is zero for the aspired attribute value. This claim has two reasons. On the one hand, the formal justification is that there is no other optimum than the score at the aspired attribute value. That holds even without restricting the domain. On the other hand, the claim implies the following property: The nearer an attribute value converges to the aspired value, the less is the increment of the score. And for the aspired attribute value the marginal increment is zero ultimately. On the other side, the more an attribute value diverges from the optimum value, the higher is the penalization. The implication is that it is harder to compensate bad attribute values (around $v_c^{min/max}$) than to get additional scores from good attribute values (around v_c^{opt}). In terms of utilities the property is known as risk avoidance. Solving the parameters *a, b, c* yields the *quadratic* scoring rule:

$$
S_c(v_c) = \begin{cases}
\lambda_c \cdot \left(1 - \left(\dfrac{v_c - v_c^{opt}}{v_c^{opt} - v_c^{min}}\right)^2\right) & , v_c^{min} \le v_c < v_c^{opt} \\
\lambda_c \cdot \left(1 - \left(\dfrac{v_c - v_c^{opt}}{v_c^{opt} - v_c^{max}}\right)^2\right) & , v_c^{opt} < v_c \le v_c^{max} \\
\lambda_c & , v_c = v_c^{opt} \\
\perp & , \text{otherwise}
\end{cases}
$$

Fig. 2 depicts the quadratic scoring rule (black graph) in comparison with the linear scoring rule (gray graph), again for the *Time* attribute, but here with $\lambda_{Ti} = 2$.

The score of the quadratic rule is steadily above the linear scoring, when considering the same weighting factors and interval boundaries. The important property, however, is that the quadratic scoring rule converges smoothly towards the optimum and diverges disproportionally in the other direction.

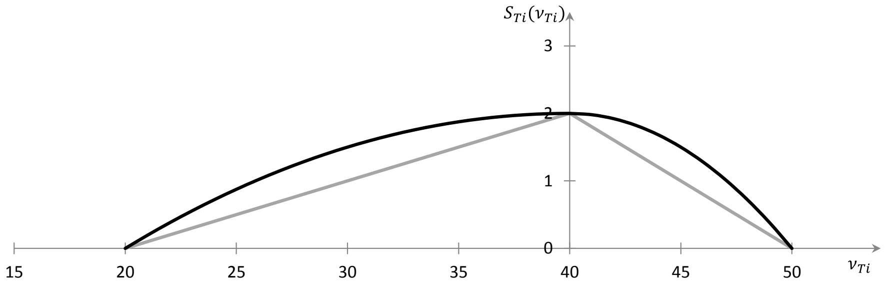

Fig. 2. Quadratic and linear scoring function in comparison (for the *Time* attribute)

4 Artifact Evaluation

4.1 Simulation Plan

The evaluation is aligned towards the research question: What is the effect of using the multi-attribute scoring rules for auctions for just-in-time deliveries? We subdivided the research question into three operational questions Q1 – Q3.

Q1: *How does the variation of the weighting factor* λ_c *affect the outcome for the attribute value* ν_c*?* In particular, we focus on *c = Time*, but also on *c = Condition*.

Q2: *How does the variation of the weighting factor* λ_c *affect the outcome for the other attribute values* ν_{-c}*?*

Q3: *What is the difference between the linear scoring rule and the quadratic scoring rule with respect to Q1 and Q2.*

So, the independent variables are the weighting factors for the *Time* attribute, and in an additional evaluation for the *Condition* attribute, too. The dependent variables are the (relative) deviations from the aspired values for each attribute. To answer the research questions Q1 – Q3 we conducted a simulation of the artifact with artificial data. So as to diminish the probability of pure coincidental results we used the averages of 1000 runs. With the confidence level of 99% the averages are less than 0.5 around the true mean for the *Time* attribute. The attribute values were drawn randomly from the settlement range Y_c for each of the *n* agents in each run. For the possible attribute values we used a uniform distribution with an integer step width of 1.

The parameterization of the simulation is based on a road pavement scenario. The condition of delivered asphalt is described by its temperature and plays a crucial role. For the sake of comparability, we normalized the resulting deviations with the highest possible deviation for the corresponding attribute value. We assume that the place is not subject for negotiation, and hence we state $Y_{Pl} = \{0\}$, $\nu_{Pl}^{min} = \nu_{Pl}^{opt} = \nu_{Pl}^{max} = 0$. That is, any deviation from $\nu_{Pl} = 0$ excludes the respective bid from the settlement range. By assumption, we regard only accepted bids, and thus omitted the *Place* attribute. The parameters for the other attributes were set as follows.

$$\begin{array}{lllll} \textit{Prize}\ [\text{€ p. ton}] & v_{\Pr}^{min}=0 & v_{\Pr}^{opt}=0 & v_{\Pr}^{max}=100 & , \\ \textit{Quantity}\ [\text{tons}] & v_{Qu}^{min}=10 & v_{Qu}^{opt}=25 & v_{Qu}^{max}=25 & , \\ \textit{Condition}\ [{}^\circ\text{C}] & v_{Co}^{min}=100 & v_{Co}^{opt}=120 & v_{Co}^{max}=160 & , \\ \textit{Time}\ [\text{minutes}] & v_{Ti}^{min}=20 & v_{Ti}^{opt}=40 & v_{Ti}^{max}=50 & . \end{array}$$

The number of bidders has naturally a positive impact on the efficiency of the results. The higher the number is, the higher is the competition. For our simulation, this fact has been incorporated by the uniformly randomized choice of the attribute values. The more bidders are simulated, the higher is the probability that the optimal bid is drawn. We took $n = 8$ delivery agents, respectively bidders, for our simulation setting, which reflects a realistic number of available dumpers at a medium sized road pavement site.

To capture the efficacy of our coordination artifact we compare the outcomes of the simulation with the expected values of the applied stochastic distribution. Since we used a discrete uniform distribution, the relative expected value of the deviation from the optimal attribute value is given by

$$\bar{v}_c^{\|\Delta\|} = \frac{\sum_{v_c = v_c^{min}}^{v_c^{max}} \left| v_c^{opt} - v_c \right|}{v_c^{max} - v_c^{min} + 1} \cdot \frac{1}{\max\left\{ v_c^{opt} - v_c^{min}, v_c^{max} - v_c^{opt} \right\}}$$

The last term of the expression normalizes the absolute deviation of the respectively aspired attribute value onto the interval [0, 1]. The resulting means are (rounded where necessary)

$$\bar{v}_{Qu}^{\|\Delta\|} = 50\%, \quad \bar{v}_{Co}^{\|\Delta\|} = 42.21\%, \quad \bar{v}_{\Pr}^{\|\Delta\|} = 50\%, \quad \bar{v}_{Ti}^{\|\Delta\|} = 42.74\%.$$

Basically, these benchmarks reflect a purely stochastically random allocation of the transport orders. The reason for the usage however is this: When weighting one particular attribute highly, we seek to figure out whether the outcome for the other attributes becomes worse than with a random allocation. Negation of this statement provides evidence for the effectivity of our artifact. As a motivational explanation, consider also the case where the transport orders are allocated beforehand in the long term, with respect to a fixed plan. Eventually, the occurrence of stochastic environmental disturbances is equivalent to a random allocation of the transport orders. Our artifact enables for short-term allocations and overcomes defects of that kind.

4.2 Simulation Results

Fig. 3 shows the resulting relative deviation for a ceteris paribus evaluation, where only the weighting factor of the *Time* attribute is varied. The other attribute values are set to 1 constantly. The results for the linear scoring rule are depicted as solid line. The dashed line depicts the results for the quadratic scoring rule. Regarding Q1 and Q2 the results match our expectation: Raising the weight for one attribute decreases

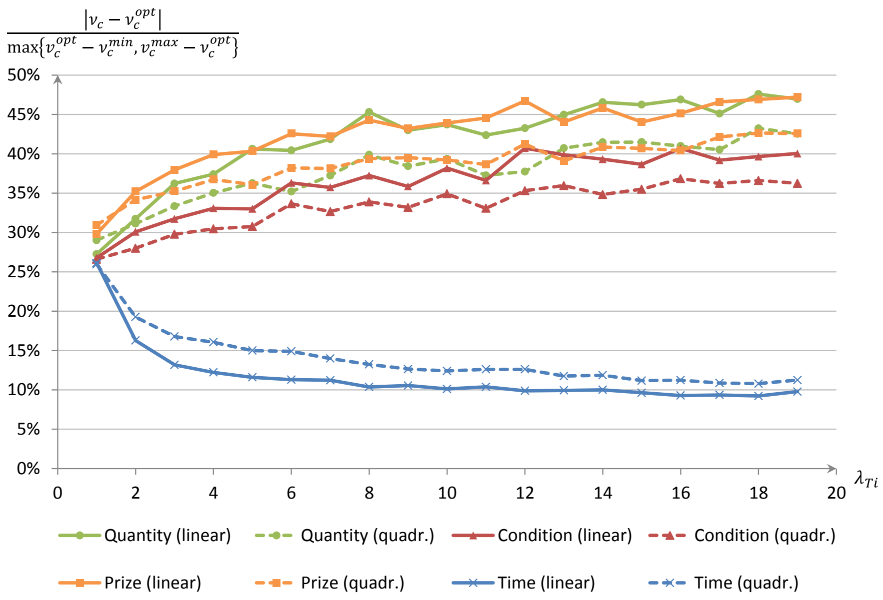

Fig. 3. Relative deviations from the aspired attribute values in dependence of the weighting factor for the *Time* (the other weighting factors are 1)

the average deviation at the cost of the average deviation for the other attributes. We can now quantify to what amount the variation of the weighting factor comes into effect. We describe in the following the results for the linear scoring rule.

The *Time* deviation converges to 10%, which is an improvement of 15% compared to the deviation with $\lambda_{Ti} = 1$. The deviation for the *Quantity* and the *Prize* converges to approx. 47%, which is a decline of about 20% compared to the smallest deviation, but still is slightly better than with a purely stochastic winner determination. The *Condition* converges to 40% declining by 15%, which is slightly better than the random allocation, too. The results, however, suggest to choose a weighting factor of 8 for the *Time* attribute, when the other attributes are weighted with 1, because the results for the *Time* deviation do not improve substantially for weights greater than 8.

Regarding Q3, the results show that the effect of varying the weighting factor is more relaxed for the quadratic scoring rule as compared to the linear scoring rule. On the one hand, the improvement for the *Time* deviation is slightly worse than with the linear scoring rule. On the other hand, the decline for the other attributes is strictly better than with the linear scoring rule. The loss of improvement for the *Time* attribute is less than the savings from the decline for the other attributes. However, the total savings add up to about only 2% – 3%.

Because in our scenario case not only the requirement of a just-in-time delivery is crucial, but also the condition, i.e. the temperature, we inquired what happens if both the weighting factors for the *Time* attribute and the *Condition* attribute are varied simultaneously, i.e. both attributes are weighted with the same factor. Fig. 4 shows

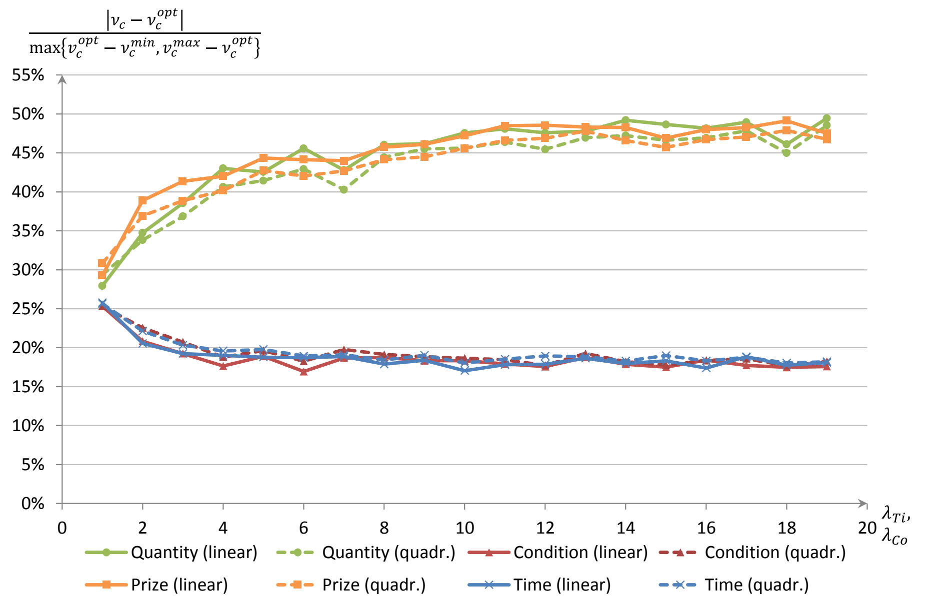

Fig. 4. Relative deviations from the aspired attribute values with simultaneous variation of the weighting factors for the *Time* and the *Condition* (the other weighting factors are 1)

the corresponding results. Now, the *Time* deviation converges only to approx. 17%. And the *Condition* deviation has now nearly exactly the same results as the *Time* deviation. For the benefits of the *Time* and the *Condition* attribute the other attributes converge now to 50%, and hence converge to the expected value with random winner determination. Nonetheless, they do not exceed the purely stochastically expected deviations. So, the decline for the *Quantity*, *Prize*, and *Time* deviation is only 3%, but the improvement for the *Condition* attribute is considerable high. That means, the consideration of a side constraint for just-in-time deliveries is effectively facilitated by our artifact. However, the results indicate that the relaxing effect of the quadratic scoring rule diminishes when weighting several attributes simultaneously.

5 Conclusion and Outlook

This research proposes a linear and a quadratic multi-attribute scoring rule for the coordination of just-in-time deliveries with an auction. The attributes for the auction reflect the general requirements for just-in-time deliveries. We have simulated our artifact to evaluate its usefulness and efficacy. We could indicate that the artifact facilitates an advantageous allocation of delivery orders. This holds in particular with respect to a side constraint (here: the *Condition* of the delivered asphalt, given by its temperature). With sole respect to the weighting factor of the *Time* attribute, we showed that the quadratic scoring rule has a relaxing effect in terms of the expected deviations from the aspired attribute values.

The coordination method accompanies a flexibilization of the order retrievals. This is in particularly beneficial to avoid tailbacks. A tailback arises, among others, due to the lack of storage place. In our pavement example, a tailback would lead to a binding of the important transport vehicles, so that shortages are the consequence.

The generally tightened competition accentuates JiT requirements for logistics providers of several industries. Mail order companies, for instance, increase their competitiveness when they deliver the orders at a point in time which is preferred by the receivers. To that end, the mail order companies can potentially choose among various deliverers. The challenge is to select the best-suited deliverer.

We see three research tasks to address limitations of our work: (1) We used a simple additive operation for the multi-attribute scoring and polynomial functions. There might be other operations or functions with different properties to inquire. (2) We evaluated a single-item auction although our model allows for combinatorial auctions, too. The question for just-in-time deliveries is, how to design a combinatorial auction to obtain optimal delivery sequences. (3) So far, we assumed truth telling for the bidders. In fact, that reliance cannot be presupposed. Further investigation must be focused on the inducement of incentive compatibility. In case of strategic bidders, the mechanism is exposed to the danger of failure.

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