

# A Multi-Agent System for Game Trading on the B2B Electronic Market

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**Abstract.** In order to provision content-based services to their users, service providers need to purchase content distribution rights from various content providers. Sometimes the creation phase of certain content categories can last longer than planned so content providers deliver the content to service providers with delays. The delayed delivery can cause financial damages and inconveniences to service providers which have already announced the appearance of new content to their users. In this paper we propose a multi-agent system which is used to model an electronic market for trading the rights to distribute video and computer games. On the proposed market, a service provider agent uses the multi-attribute reputation decision making mechanism to purchase content distribution rights from content provider agents. Several sets of experiments were conducted to demonstrate the efficiency of the multi-attribute reputation decision making mechanism.

**Keywords:** content trading, B2B content e-market, reputation tracking auctions, multi-agent system

## 1 Introduction

The ability to transfer various video and audio data as well as other forms that carry certain information into digital form so it can be deployed across multiple technologies is considered to be one of the fundamental enablers of convergence between different domains (i.e., telecommunications, the Internet, information technology, broadcasting and media) that are involved in the content service provisioning process [3, 13]. The appearance of digital content was followed by the development of (digital) content market while the advances in the ICT (Information and communication technologies) industry enabled the development of (digital) content electronic market (e-market).

Service providers (i.e., network operators, internet service providers, cable television operators) recognized the potential of the content e-market and started to develop new business models for provisioning content-based services to their users [1, 5, 6]. The term content encompasses movies, songs, games, news, images and text, in other words data and information within various fields [12]. Since content production is not in service providers' primary business domain, in order

to provision content-based services, they have to buy content distribution rights from various content providers (i.e., media companies, copyright holders) on the content e-market [1, 4]. Content providers sell content distribution rights to service providers on the Business-to-Business (B2B) content e-market, while service providers provision content-based services to users on the Business-to-Consumer (B2C) content e-market [7, 10].

Games are one of the youngest content categories while the (digital) games market is considered to be one of the most advanced content markets when it comes to digital distribution and exploitation [11]. Some content categories, such as games, have longer and/or expensive creation phases so content providers can sell content distribution rights on the B2B content e-market during the creation phase even before the content is finished (e.g., game distribution rights can be sold once the story line has been created and the visuals of the game have been designed). If the creation phase lasts longer than anticipated by the creation deadlines, games can be delivered to service providers with delays causing financial damages and inconveniences to service providers.

The paper is organized as follows. Section 2 presents the architecture of a multi-agent system for game trading while section 3 presents the settings of the conducted experiments and the obtained results. Section 4 concludes the paper and gives an outline for future work.

## 2 Architecture of the Multi-Agent System

Figure 1 shows the architecture of the proposed multi-agent system for game trading that is defined as  $MAS_{gt} = \{SPA, CPA_1, \dots, CPA_i, \dots, CPA_M\}$ . The Service Provider Agent  $SPA$  represents a network operator which acts as a service provider on the content e-market while  $M$  Content Provider Agents  $CPAs$  represent game publishing companies which publish (and produce) games and act as content providers on the B2B content e-market. On the B2C content e-market, the  $SPA$  provides game-based services to users which are represented by their User Agents ( $UAs$ ).

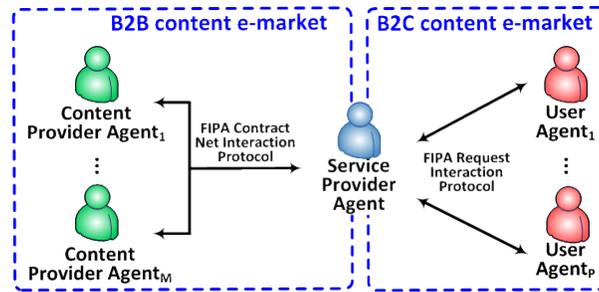


Fig. 1. Architecture of the multi-agent system for games trading

### 2.1 Content Provider Agent

The content provider agent  $CPA_i$  sells game distribution rights to the  $SPA$ . The  $CPA_i$  is defined as follows  $CPA_i = \{\mathbf{X}_{cpa_i}, dem, r_c(i)\}$  where  $\mathbf{X}_{cpa_i}$  represents the current  $CPA_i$ 's games offer,  $dem$  stands for the delivery evaluation mechanism which is used to calculate the on-time delivery probability for a certain game, while the  $r_c(i)$  is the  $CPA_i$ 's risk taking policy which represents the lowest acceptable value of the on time delivery probability defined by the game publishing company's business strategies.

The  $CPA_i$  receives a Call For Proposals (CFP) from the  $SPA$  and decides whether it will participate in an auction held by the  $SPA$ . If the  $CPA_i$  does not have at its disposal any games ready for distribution, it calculates the on-time delivery probability  $p(t_c(\mathbf{x}_i))$  that the creation phase of a certain game  $\mathbf{x}_i \in \mathbf{X}_{cpa_i}$  will be completed by the deadline  $t_c$  which is defined in the CFP. If the probability  $p(t_c(\mathbf{x}_i))$  is higher than its risk taking policy  $r_c(i)$ , the  $CPA_i$  sends an offer  $\mathbf{x}_i$ .

### 2.2 Service Provider Agent

The  $SPA$  is defined as follows  $SPA = \{th, gc, cem, rtm, mrdm\}$ , where the  $th$  is the trading history with  $CPAs$ , the  $gc$  contains information about prior users' games consumption, the  $cem$  is the content evaluation mechanism, the  $rtm$  is the reputation tracking mechanism while the  $mrdm$  is the multi-attribute reputation decision making mechanism. The information from the  $th$  is gathered from prior transactions with  $CPAs$  and used by the  $rtm$ . The information contained in the  $gc$  is gathered from users' consumption behaviour on the B2C e-content market and used to determine reserve and aspiration values used by the  $cem$ .

After analysing the information from the  $gc$ , the  $SPA$  determines relevant game attributes  $\mathbf{A} = \{a_1, \dots, a_j, \dots, a_n\}$  as well as their reserve and aspiration values necessary for the evaluation of games offered by  $CPAs$ . Reserve value  $x_j^r$  marks the lowest value of an attribute  $a_j$  that is acceptable to the  $SPA$  while the aspiration value  $x_j^a$  is the highest value of an attribute  $a_j$  that the  $SPA$  is interested in. The  $SPA$  starts an auction by sending CFPs to  $CPAs$ . The  $SPA$  acts as a buyer while  $CPAs$  act as sellers in the auction. The required delivery deadline  $t_c$  as well as a list of relevant attributes  $\mathbf{A}$  and their reserve values  $\mathbf{x}^r = \{x_1^r, \dots, x_j^r, \dots, x_n^r\}$  are sent within the CFP. The  $SPA$  receives  $m \leq M$  offers  $\mathbf{X}_m = \{\mathbf{x}_1, \dots, \mathbf{x}_i, \dots, \mathbf{x}_m\}$  from  $CPAs$  that decided to participate in the auction where the  $CPA_i$  offers to sell distribution rights of the game  $\mathbf{x}_i = \{x_{i1}, \dots, x_{ij}, \dots, x_{in}\}$ .

**Content Evaluation Mechanism** The  $cem$  [9] is represented with a tuple  $\langle \mathbf{X}_m, w_c, u_c, d, u \rangle$ , where each offer  $\mathbf{x}_i = \{x_{i1}, \dots, x_{ij}, \dots, x_{in}\}$  from the set of offers  $\mathbf{X}_m$  is described with  $n$  attributes,  $w_c = \{w_{c1}, \dots, w_{cj}, \dots, w_{cn}\}$  is a set of weights that determines the importance of each attribute from  $\mathbf{x}_i$ ,  $u_c$  is a utility function that calculates the  $SPA$ 's utility of  $CPA_i$ 's offer  $\mathbf{x}_i$ ;  $d$  is a deviation function that calculates the  $SPA$ 's additional benefit of  $CPA_i$ 's offer

$\mathbf{x}_i$ ;  $u$  is a utility function that calculates the total utility of the offer  $\mathbf{x}_i$  and it is defined as follows:

$$u(\mathbf{x}_i) = (1 - w_{c,bonus})u_c(\mathbf{x}_i) + w_{c,bonus}d(\mathbf{x}_i). \quad (1)$$

The primary objective of the  $u(\mathbf{x}_i)$  is to maximize content utility  $u_c(\mathbf{x}_i)$  of the offered content  $\mathbf{x}_i$  while the secondary objective is to maximize additional benefits  $d(\mathbf{x}_i)$  that an offer brings. The weight of additional benefits  $w_{c,bonus}$  should be low enough to prevent a *CPA* with an average offer from manipulating the auction outcome in its favour, but at the same time it should reward a *CPA* with a very good offer which also brings additional benefits to the *SPA*.

The content utility function  $u_c(\mathbf{x}_i)$  is an additive scoring function that assumes the existence of mutual *preferential independence* between attributes [2]. It is defined as follows:

$$u_c(\mathbf{x}_i) = \sum_{j=1}^n w_{c_j} u_c(x_{ij}), \text{ where } \sum_{j=1}^n w_{c_j} = 1 \quad (2)$$

$$u_c(x_{ij}) = \begin{cases} \frac{x_{ij} - x_j^r}{x_j^a - x_j^r}, & x_j^r \neq x_j^a \ \& \ x_j^r \leq x_{ij} \leq x_j^a \\ \text{N.A.}, & x_{ij} < x_j^r \\ 1, & x_{ij} > x_j^a \end{cases} \quad (3)$$

Value N.A. in (3) marks a non-acceptable value for an attribute. Values offered higher than the aspiration value are acceptable, but their utility cannot be higher than 1. The positive deviation function  $d(\mathbf{x}_i)$  compares an offer  $\mathbf{x}_i$  placed by the  $CPA_i$  with the aspiration offer  $\mathbf{x}^a = \{x_1^a, \dots, x_j^a, \dots, x_n^a\}$  taking into consideration highest possible attribute values  $x_j^{max}$  as follows:

$$d(\mathbf{x}_i) = \sqrt{\sum_{j=1}^n d(x_{ij})^2}, \quad d(x_{ij}) = \begin{cases} w_{c_j} \frac{x_{ij} - x_j^a}{x_j^{max} - x_j^a}, & \text{if } x_{ij} > x_j^a \ \& \ x_j^a \neq x_j^{max} \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

**Reputation Tracking Mechanism** The *rtm* [8] is represented with a tuple  $\langle y, w_r, V, r \rangle$ , where  $y = \{y_1, y_2, y_3\}$  is a set of attributes used to calculate *CPAs'* reputation,  $w_r = \{w_{r1}, w_{r2}, w_{r3}\}$  is a set of weights that determines the importance of each attribute from  $y$  for the *SPA*,  $V$  is the *SPA's* sliding window which is used to store information regarding the last  $v$  auctions the *SPA* held; and  $r$  is a utility function that calculates *CPAs'* reputation.

Three attributes relevant for calculating  $CPA_i$ 's reputation are:  $y_1$  – the average utility of games the  $CPA_i$  offers;  $y_2$  – the share of total transactions carried out by the  $CPA_i$ ;  $y_3$  – the share of financial damages inflicted on the *SPA* due to  $CPA_i$ 's late delivery. The formulas for calculating reputation are as follows:

$$r(CPA_i) = \sum_{l=1}^3 w_{r_l} y_l = w_{r1} \frac{1}{a_i} \sum_{k=1}^v \frac{a_i^k u(\mathbf{x}_i^k)}{u(\mathbf{x}_{y_i n}^k)} + w_{r2} \frac{\sum_{k=1}^v c_i^k n_k p_k x_{i1}^k}{\sum_{k=1}^v n_k p_k x_{win,1}^k} + w_{r3} \left(1 - \frac{\sum_{k=1}^v c_i^k a_i^k}{\sum_{s=1}^m \sum_{k=0}^v c_s^k d_i^k}\right), \text{ where } : \sum_{l=1}^3 w_{r_l} = 1 \quad (5)$$

$$a_i = \sum_{k=1}^v a_i^k, a_i^k = \begin{cases} 1, & \text{if } CPA_i \text{ participated in auction } k \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

$$c_i^k = \begin{cases} 1, & \text{if } CPA_i \text{ won in auction } k \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

$$d_i^k = n_{k1} p_k x_{i1}^k \quad (8)$$

In (5),  $\mathbf{x}_{win}^k$  denotes the winning offer in auction  $k$ ,  $n_k$  denotes how many times has the  $SPA$  sold a certain game,  $p_k$  denotes the selling price of a game, while  $x_{i1}^k$  is the percentage of the income from selling games that the  $SPA$  will get,  $a_i^k$  in (6) denotes  $CPA_i$ 's participation in auction  $k$ ;  $c_i^k$  in (7) denotes whether the  $CPA_i$  won auction  $k$ . In (8),  $d_i^k$  denotes the estimated financial damage inflicted to the  $SPA$  due to the  $CPA_i$ 's late delivery while  $n_{k1}$  denotes the estimated number of users that would have bought the game in the period between the arranged and actual delivery date.

**Multi-attribute Reputation Decision Making Mechanism** The  $mrdm$  is defined as a tuple  $\langle cem, rtm, w_t, t \rangle$  where  $cem$  and  $rtm$  are previously described content evaluation mechanism and reputation tracking mechanism, respectively,  $w_t = \{w_{t1}, w_{t2}\}$  denotes a pair of weights where  $w_{t1}$  and  $w_{t2}$  determine the importance of  $cem$  and  $rtm$ , respectively, and  $t$  is the total score function. The winner of the  $SPA$ 's auction is the  $CPA_i$  with the highest total score  $t(\mathbf{x}_i)$  which is determined as follows:

$$t(\mathbf{x}_i) = w_{t1}u(\mathbf{x}_i) + w_{t2}r(cpa_i), \text{ where } w_{t1} + w_{t2} = 1 \quad (9)$$

### 3 Case study: Games trading

The proposed multi-agent system was implemented using the Java Agent Development Framework (JADE<sup>1</sup>) and it consists of one  $SPA$  and 8  $CPAs$ . The  $SPA$  conducts auctions by using the *FIPA Contract Net Interaction Protocol*<sup>2</sup>.

In this case study publishing companies announce the appearance of new games roughly one month earlier while the service provider offers few new games to its users every day what comes up to 25 games in one week. So, each week the  $SPA$  conducts 25 sequential auctions and purchases the rights to distribute games which the service provider is going to start offering to his users during one week in the next month. Since the service provider announces the appearance of new games to its users it is important that the games are delivered on time.

Before the beginning of an auction, the  $SPA$  determines relevant attributes and their appropriate (i.e., reserve and aspiration) values which are going to be used for the evaluation of offered games. Those attributes are:  $a_1$  - a percentage

<sup>1</sup> <http://jade.tilab.com>

<sup>2</sup> <http://www.fipa.org/specs/fipa00029/index.html>

**Table 1.** Range of attribute values and *SPA*'s attribute valuations

	$a_1$	$a_2$	$a_3$	$a_4$	$a_5$
minimum value ( $x_j^{min}$ )	0	$t_1$	0	0	1
maximum value ( $x_j^{max}$ )	100	$t_8$	100	100	100
weight ( $w_j$ )	0.30	0.25	0.20	0.15	0.10
reservation value ( $x_j^r$ )	15	$t_1$	50	15	30
aspiration value ( $x_j^a$ )	40	$t_8$	90	45	75

of income from each sold game that the *SPA* will get,  $a_2$  - game type,  $a_3$  - a percentage of mobile phone types which have the necessary software and hardware support to run the offered game,  $a_4$  - a percentage of income from selling various advanced game options that the *SPA* will get, and  $a_5$  - the time period during which the *SPA* has the right to sell the game.

Table 1 contains the minimum (i.e., worst) and maximum (i.e., best) possible attribute values as well as *SPA*'s valuations (i.e., weights), reservation and aspiration values for each attribute. Minimum and maximum values as well as *SPA*'s valuations of all attributes remained the same during the experiment. We assume that the game will not be interesting to users longer than three months so we set the  $x_5^{max}$  on 100 days even though  $x_5^{max}$  can actually be indefinite. Game types are taken from Ovi<sup>3</sup>:  $t_1$  - action,  $t_2$  - arcade,  $t_3$  - education,  $t_4$  - card & casino,  $t_5$  - adventure,  $t_6$  - puzzle and trivia,  $t_7$  - sports, and  $t_8$  - strategy.

After the  $CPA_i$  receives a CFP it determines the probability that the game  $\mathbf{x}_i$  will be completed on time. If the probability is higher than its risk taking policy  $r_c(i)$ , the  $CPA_i$  offers the game  $\mathbf{x}_i$  to the *SPA*. In this case study the  $CPA_i$ 's on time delivery probability for a game  $\mathbf{x}_i$  in the auction  $k$  is determined by (10) while the  $CPA$ 's risk taking policies are listed in Table 2.

$$p_k(t_c(\mathbf{x}_i)) = p_{k-1}(t_c(\mathbf{x}_i)) + \text{random}[-0.05, 0.05] \quad (10)$$

**Table 2.** Content providers' risk taking policies

agent	$CPA_1$	$CPA_2$	$CPA_3$	$CPA_4$	$CPA_5$	$CPA_6$	$CPA_7$	$CPA_8$
$r_c(i)$	0.6	0.65	0.7	0.8	0.55	0.6	0.65	0.7

Aspiration and reserve values are determined from game sales records. Since we do not model users behaviour, in this experiment reserve and aspiration values were chosen randomly from intervals  $[0.95x_j^r(nominal), 1.05x_j^r(nominal)]$  and  $[0.95x_j^a(nominal), 1.05x_j^a(nominal)]$ , respectively, after each set of 25 auctions. The values  $x_j^r(nominal)$  and  $x_j^a(nominal)$  are given in Table 1. The *SPA*

<sup>3</sup> <https://store.ovi.com/#/games>

accepted offers containing all game types. The utility of a certain game type  $t_j$  was equal to its market share in the last period  $\delta t$  (i.e. last week) as follows:

$$u_c(x_{i2}) = n_{t_j}(\delta t) / \sum_{j=1}^8 n_{t_j}(\delta t), \quad (11)$$

while the number of games sold in one week  $n_{t_j}(\delta t)$  for each game type  $t_j$  was chosen randomly from the interval  $[0.8n_{t_j}(\textit{nominal}), 1.2n_{t_j}(\textit{nominal})]$  where  $n_{t_j}(\textit{nominal})$  for all games type was 12500.

*CPAs* also calculate their reserve and aspiration values from game sales records so those values do not differ significantly from the values calculated by the *SPA*. *CPAs*' reserve and aspiration values are chosen randomly from intervals  $[0.95x_j^r(\textit{nominal}), 1.05x_j^r(\textit{nominal})]$  and  $[0.95x_j^a(\textit{nominal}), 1.05x_j^a(\textit{nominal})]$ , respectively, while their nominal values are given in Table 3. The *CPAs* offer values that are chosen randomly between *CPAs*' reserve and aspiration values.

**Table 3.** Content provider agents' weights, reserve and aspiration values

Attribute	$a_1$	$a_2$	$a_3$	$a_4$	$a_5$	$a_1$	$a_2$	$a_3$	$a_4$	$a_5$
	Content Provider Agent $CPA_1$					Content Provider Agent $CPA_2$				
$w_{cj}$	0.35	0.21	0.15	0.20	0.09	0.34	0.19	0.145	0.21	0.115
$x_j^r$	37.5	$t_1$	38	90	45	36	$t_1$	34	88	41
$x_j^a$	12.5	$t_8$	24	60	85	14	$t_8$	16	61	86
	Content Provider Agent $CPA_3$					Content Provider Agent $CPA_4$				
$w_{cj}$	0.33	0.18	0.175	0.19	0.125	0.36	0.24	0.16	0.175	0.085
$x_j^r$	38	$t_1$	33.5	92	49	37.5	$t_1$	34.5	87	43
$x_j^a$	13	$t_8$	14	58	90	15.5	$t_8$	13	63	91
	Content Provider Agent $CPA_5$					Content Provider Agent $CPA_6$				
$w_{cj}$	0.345	0.22	0.14	0.165	0.13	0.335	0.21	0.155	0.185	0.125
$x_j^r$	39	$t_1$	33	85	47	36.5	$t_1$	37	83	46
$x_j^a$	16	$t_8$	12	54	88	13	$t_8$	11	57	89
	Content Provider Agent $CPA_7$					Content Provider Agent $CPA_8$				
$w_{cj}$	0.36	0.23	0.13	0.15	0.13	0.375	0.19	0.21	0.115	0.11
$x_j^r$	38.5	$t_1$	35.5	94	44	37.5	$t_1$	38.5	92	48
$x_j^a$	13.5	$t_8$	15	67	87	14.5	$t_8$	16	59	90

Once the *SPA* chooses the winning  $CPA_i$  of auction  $k$ , whether the  $CPA_i$  will deliver the game on time or with a delay is determined as defined in Listing 1. In case the delivery delay occurs, the number of users  $n_{k1}(\mathbf{x}_i)$  that would have bought the game  $\mathbf{x}_i$  in the period between the agreed and actual delivery time is calculated as follows:

$$n_{k1}(\mathbf{x}_i) = n_k(\mathbf{x}_i) * (1 - e^{(1-temp)}), \quad (12)$$

where the variable *temp* is taken from Listing 1 while the total number of users  $n_k(\mathbf{x}_i)$  that would have bought the game  $\mathbf{x}_i$  if it was delivered on time is deter-

**Listing 1** The on time delivery occurrence

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temp = random[0, 1]
if temp < pk(xi) then
  on time delivery
else
  delivery delay
end if

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mined by (13) where  $t_j$  is the game type of game  $\mathbf{x}_i$ .

$$n_k(\mathbf{x}_i) = \frac{\sum_{l=((k \bmod 25)-1) \cdot 25+1}^{(k \bmod 25) \cdot 25} n_l(\mathbf{x}_i^l)}{|n_l(\mathbf{x}_i^l \mid x_{i2} = t_j)|} \cdot \frac{u(\mathbf{x}_i^l)}{\frac{1}{25} \sum_{l=((k \bmod 25)-1) \cdot 25+1}^{(k \bmod 25) \cdot 25} u_l(\mathbf{x}_i^l \mid i=\text{winner})} \quad (13)$$

The total *SPA*'s income from selling a game  $\mathbf{x}_i$  bought in auction  $k$  is:

$$\text{income}_{r/nr,k}(\mathbf{x}_i) = (n_k - n_{k1}) \cdot p_k \cdot x_{i1} \quad (14)$$

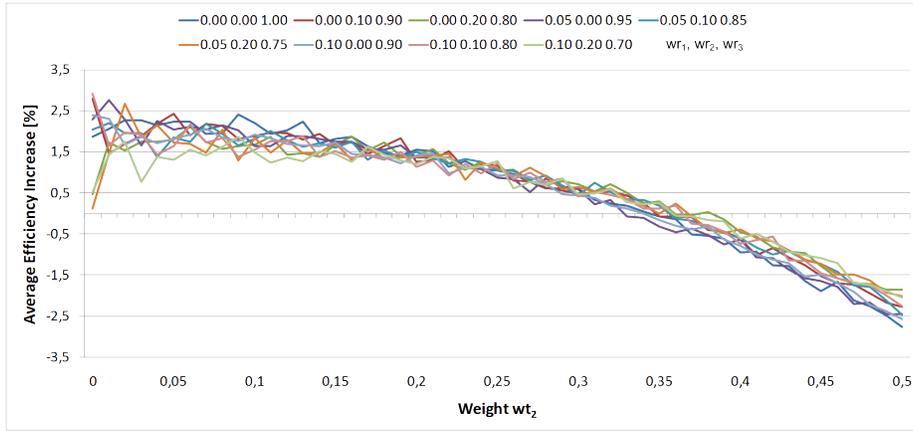
where the label  $r/nr$  specifies whether the *SPA* took the *CPA*'s reputation into account (label  $r$ ) when it determined the winner of the auction, or did not (label  $nr$ ),  $p_k$  is the game unit price while the  $x_{i1}$  is the percentage of the total income that the *SPA* keeps from the game sales.

For each auction in the experiment we determined the winner of the auction by using the multi-attribute reputation decision making mechanism and calculated the income  $\text{income}_r$  from the game sales by using (14). For each auction we also determined the winner by using just the content evaluation mechanism (i.e., the weight  $w_{t2}$  in (9) was set to 0 so the *CPAs*' reputation was not taken into account) and calculated the accompanying income  $\text{income}_{nr}$ . The efficiency  $\eta$  of the reputation tracking mechanism is determined by comparing the previously defined incomes as follows:

$$\eta = \frac{\sum_{k=1}^T \text{income}_{r,k}(\mathbf{x}_i^k) - \sum_{k=1}^T \text{income}_{nr,k}(\mathbf{x}_j^k)}{\sum_{k=1}^T \text{income}_{nr,k}(\mathbf{x}_j^k)}, \forall k \text{ when } \text{cpa}_i \neq \text{cpa}_j. \quad (15)$$

where  $T$  is the total number of reputation tracking auctions in one experiment.

We conducted nine sets of experiments as follows. We changed the values of reputation attribute weights (i.e.,  $w_{r1}$ ,  $w_{r2}$  and  $w_{r3}$ ) in each set and conducted 100 series of experiments per set. Each series of experiments is conducted with different total attribute weights (i.e.,  $w_{t1}$ ,  $w_{t2}$ ). In the first series the weight  $w_{t2}$  is set to 0.01 and it is increased in each following series by 0.01. One series of experiments consists of 100 experiments while one experiment includes 2800 seal-bid multi-attribute reverse auctions held sequentially one after the other. Since the reputation in an ongoing auction was calculated from the trading history gathered from previous 300 auctions, the first 300 out of 2800 auctions did not take reputation into account when determining the winner of an auction but they were used to calculate *CPAs*' reputations later. The remaining 2500 auctions



**Fig. 2.** Efficiency of the reputation tracking mechanism

took reputation into account when determining the winner of the auction. In the conducted experiments we tried to increase *SPA*'s income by reducing the damages inflicted to the *SPA* as a consequence of *CPAs*' late deliveries. The emphasis was put on the reputation attribute  $y_3$  by setting a higher value of reputation attribute weight  $w_{r3}$ .

In Figure 2 we can see the results of the conducted experiments. At the end of each experiment the efficiency of the reputation tracking mechanism is calculated by using (15). Since one series consists of 100 experiments, Figure 2 shows a mean value of efficiency for each series. The efficiency of the reputation tracking mechanism varies between 1.5 and 2.5% for weights  $w_{t2} \in [0.05, 0.15]$  and continues to decrease afterwards. Approximately after the  $w_{t2}$  rises above 0.35 the reputation tracking mechanism becomes inefficient (i.e.,  $\eta < 0$ ).

## 4 Conclusion and Future Work

The presented multi-attribute reputation decision making mechanism enables service providers to negotiate the purchase of content distribution rights by taking into account content attributes as well as the content providers' reputation. The reputation is based on: i) the utility of content providers' offered content in previous auctions what gives a certain advantage to content providers which offer high quality content; ii) the ratio of incomes realized from selling content of a certain content provider and service provider's total income; and iii) the ratio of damages that a certain content provider caused with its delayed content deliveries and the total damages caused by all content providers. We implemented a multi-agent system in which the Service Provider Agent uses the proposed multi-attribute reputation decision making mechanism to purchase game distribution rights from Content Provider Agents on the B2B e-content market.

From the conducted experiments we can see that the efficiency of the proposed mechanism varies between 1.5 and 2.5% when the importance of the reputation in the decision making process varies between 5 and 15% while the mechanism becomes inefficient when the importance of the reputation rises above 35%.

For future work we plan to model several strategies which content providers will use to prepare offers and continue our work with modelling users behaviour to get a complete content electronic market.

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## References

1. Bang, Y.H.: Nom 2.0: innovative network operations and management for business agility. *IEEE Communications Magazine* 46(3), 10–16 (2008)
2. Bichler, M.: An experimental analysis of multi-attribute auctions. *Decision Support Systems* 29(3), 249–268 (2000)
3. Hanrahan, H.: *Network Convergence: Services, Applications, Transport, and Operations Support*. John Wiley & Sons, Inc., New York, NY, USA (2007)
4. LeClerc, M.: Swimming with the sharks. *Ericsson Business Review* 2(3), 18–22 (2007)
5. Olla, P., Patel, N.V.: A value chain model for mobile data service providers. *Telecommunications Policy* 26(9-10), 551–571 (2002)
6. Petersson, J., Strömberg, B.: The key to value-adding the connected home. *Ericsson Business Review* 4(1), 40–42 (2009)
7. Petric, A.: A Multi-Agent System for Content Trading in Electronic Telecom Markets Using Multi-Attribute Auctions. In: Simperl, E. (ed.) *10th International Conference on Electronic Commerce ICEC'08 Proceedings of the Doctoral Consortium*. pp. 1–5 (2008)
8. Petric, A., Jezic, G.: Reputation tracking procurement auctions. In: Nguyen, N.T., Kowalczyk, R., Chen, S.M. (eds.) *ICCCI. LNCS*, vol. 5796, pp. 825–837. Springer, Heidelberg (2009)
9. Petric, A., Jezic, G.: Multi-attribute auction model for agent-based content trading in telecom markets. In: Setchi, R., Jordanov, I., Howlett, R., Jain, L. (eds.) *Knowledge-Based and Intelligent Information and Engineering Systems*, vol. 6276, pp. 261–270. Springer (2010)
10. Podobnik, V., Petric, A., Trzec, K., Jezic, G.: Software Agents in New Generation Networks: Towards the Automation of Telecom Processes. In: *Knowledge Processing and Decision Making in Agent-Based Systems*. pp. 71–99 (2009)
11. Screen Digest, Rightscom, Goldmedia, CMS Hasche Sigle: *Interactive content and convergence: Implications for the information society*. Screen Digest Limited, London, UK (2006)
12. Subramanya, S., Yi, B.K.: Utility Model for On-Demand Digital Content. *Computer* 38, 95–98 (2005)
13. Wu, I.: Canada, south korea, netherlands and sweden: regulatory implications of the convergence of telecommunications, broadcasting and internet services. *Telecommunications Policy* 28(1), 79–96 (2004)