A Game-Theoretic Approach to Decision Support for Intelligent Water Distribution

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Abstract—Cyber-physical systems, and the intelligent decision support systems that they enable, carry the promise of greater efficacy in environmental management. The complexity of the physical infrastructure subject to decisions by environmental management systems is often an impediment to this efficacy. Other challenges include fundamental differences in the operation of cyber and physical components, and significant inter-dependency among the cyber components that facilitate decision support and the physical components they control. The agent-based computing paradigm is proposed for surmounting these challenges, due to the flexibility of software agents as autonomous and intelligent decision-making components. In this paper, we utilize an agent-based system to illustrate the application of game theory to decision support for environmental management, in the context of intelligent water distribution. Simulation results are presented to validate the model proposed, and to investigate the effect of various model parameters on water allocation.

Index Terms—decision support system; environmental management; cyber-physical systems; game theory

I. INTRODUCTION

The intelligent decision support facilitated by the use of information systems, i.e., cyber infrastructure, carries the promise of better utilization of limited environmental resources. Tight integration of the cyber infrastructure with the underlying physical components served by decision support has led to the development of cyber-physical systems (CPSs), where embedded computing and communication capabilities are used to streamline and fortify the operation of a physical system [1], [2]. In CPSs, sensors collect information about the physical operation of the system, and communicate this information in real-time to the computers and embedded systems used for intelligent control. These cyber components use computational intelligence to process the information and determine appropriate control settings for physical components of the system, such as devices used to control the flow of a physical commodity, e.g., water or electric power, on a line.

Public safety concerns and prohibitive cost necessitate the use of modeling and simulation for validation of intelligent environmental decision support systems (EDSSs). Among the techniques available, agent-based modeling holds particular promise in surmounting the challenges of representing both cyber and physical components, with high fidelity, in one system; and characterizing their interaction quantitatively. This is due to the capability of an agent-based model to encapsulate diverse component attributes within a single agent, while accurately capturing the interaction among autonomous, heterogeneous agents that share a common goal achieved in a distributed fashion. Sensors are key to this approach, as they provide situational awareness to the agents and enable them to function based on the semantics of their mission and the specifics of their environment.

In this paper, we present an agent-based framework for intelligent environmental decision support. The specific environmental management problem addressed is water distribution, i.e., the allocation of water to different consuming entities by an intelligent water distribution network (WDN). In a WDN, physical components, e.g., valves, pipes, and reservoirs, are coupled with the hardware and software that supports intelligent water allocation. Fig. 1 depicts an example.

The primary goal of WDNs is to provide a dependable source of potable water to the public. Information such as demand patterns, water quantity (flow and pressure head), and water quality (contaminants and minerals) is critical in achieving this goal, and beneficial in guiding maintenance efforts and identifying vulnerable areas requiring fortification and/or monitoring. Sensors dispersed in the physical infrastructure collect this information, which is processed and interpreted by distributed algorithms running on the cyber infrastructure. These algorithms provide decision support to hardware controllers that are used to manage the allocation (quantity) and chemical composition (quality) of the water. The algorithms are implemented through software executing on multiple distributed computing devices. This software is represented by the agents in our model, each of which is capable of perceiving its environment, acting on that perception, and communicating with other agents.

The work presented in this paper investigates the adoption of game theory as the algorithmic technique used for agent-based decision support in an intelligent WDN. The focus is on management of the quantity of water allocated to each consuming entity. Game theory is a natural choice for complex resource allocation problems such as water distribution, where hydraulic and physical constraints, ethical concerns, and economic considerations should be represented in decision support. Our proposed approach is based on the utilization of game theory for resource sharing and service provision in peer-to-peer networks [3].
II. RELATED WORK

The utilization of EDSSs in managing critical infrastructure has been investigated in numerous studies. A general introduction to integrated decision support systems for environment planning is provided in [4]. Applications of EDSSs include prevention of soil salinization [5], regional environment risk management in municipal areas [6], and environmental degradation monitoring [7]. Examples particularly relevant to this paper are [8], which presents an integrated EDSS for water resource utilization and groundwater control; and [9], which defines the major functionalities for an EDSS dedicated to the hydraulic management of the Camargue ecosystem. Discussion on available models and tools, such as GIS, and database management systems, is presented in [10], which also presents an application of biogeochemical modeling for sustainability management of European forests.

Resource management algorithms have also been proposed for intelligent regulation. For instance, hedging rules have been utilized to minimize the impact of drought by effectively reducing the ongoing water supply to balance the target storage requirement [11]. Applications of game theory include optimization of rate control in video coding [12], allocation of power in frequency-selective unlicensed bands [13], and power control in communications [14]. Most relevant to this paper is the use of game theory in analyzing water resources for optimal allocation [15]. Unlike our work, where the focus is to enable environmental management, specifically water allocation, through the use of CPSs; the focus of [15] is on incorporating social and economic factors to provide a solution that maximizes the overall value of water resources while satisfying both administrative resources allocation mandates and consumer requirements.

This paper presents an EDSS, with the broader goal of applying the insights gained to similar CPSs. Many CPSs, especially critical infrastructure systems, can be viewed as commodity transport networks. WDNs are an example, as are smart grids and intelligent transportation systems. The commodity transported varies from one domain to another, but the systems share the goal of allocating limited resources under physical constraints, and leverage the intelligent decision support provided by cyber infrastructure in achieving this goal. As an emerging research area, the body of literature specifically related to CPSs is limited. A considerable fraction of related work examines critical infrastructure systems. Salient studies include [16], which investigates interdependencies among different components of critical infrastructure systems, and [17], which provides a relatively comprehensive summary of modeling and simulation techniques for critical infrastructure systems. Related challenges are enumerated in [18], where system complexity is identified as the main impediment to accurate characterization of CPSs. Our work is one of few studies in the emerging field of CPSs to go beyond qualitative characterization of the system to quantitative analysis.

III. INTELLIGENT WATER ALLOCATION AS A GAME

A. Model of the service game

In this section, we model the interaction among selfish agents as a service game, using the notation of [3], where the service game presented models resource sharing in peer-to-peer networks. We divide time, $t$, into discrete numbered slots, e.g., $t = 0$ or $t = 1$. During each time slot, each agent can receive requests for service from other agents, or request...
their services for itself. The service in question here is the provision of water. The quality of the water provided is beyond the scope of this paper; our focus is on quantity. The model presented in this paper is a first step that seeks to demonstrate the feasibility of an agent-based implementation of an EDSS based on game theory. In this preliminary model, we assume an unlimited water supply. This assumption is justified in cases where water resources are not scarce, and the aim of decision support is to facilitate more efficient water distribution. Future work will investigate the application of game theory to a WDN with limited water supply.

Each request issued by an agent can be sent to more than one service provider (peer agent), to increase the probability that the request will be fulfilled. For a service provider, the incoming requests can arrive either in parallel or in sequence. A request will stop propagating among the agents when any of the providers agree to serve, at which point the request is considered to have been fulfilled. For simplicity, we assume that an agent can submit only one service request and can accommodate only one service request during a time slot. An agent’s status for a given time slot is labeled as \(Srv\) if it fulfills any of the requests received during the time slot. The status of all agents and requests is propagated throughout the system. The cycle of service request and provision repeats indefinitely, which corresponds to an infinitely repeated game, \(G^\infty\), where the basic game being repeated is \(G\).

More specifically, the basic game, \(G\), is defined in terms of the following items:

- Players: all peer agents that participate in water allocation; for tractability, peer agents are assumed to be identical.
- Actions: each agent can decide for or against service provision, denoted as \(Srv\) and \(Dcln\), respectively.
- Preference of each player: represented by the expected value of a payoff function determined by the action taken. When service is received by an agent, the payoff value of the agent denoted as utility, \(U\); when the agent provides service, the payoff value is denoted as cost, \(C\).

The reputation of a player, \(i\), in a given time slot, \(t\), is denoted by \(R(t, i)\), and depends on whether or not it provides service, both in the current time period and in prior periods, as represented by Equation 1:

\[
R(t, i) = R(t-1, i) \ast (1-a) + (w \ast a), \quad 0 \leq a \leq 1, t \geq 2
\]

If service is provided by player \(i\) in time period \(t\), \(w\) is set to 1, otherwise 0. The reputation of all players is initialized as 0 at time \(t = 0\), and is defined as \(w\) at \(t = 1\). Therefore, \(0 \leq R(t, i) \leq 1\) is always maintained. In Equation 1, parameter \(a\) is a constant that captures the strength of the “memory of the system,” i.e., the relative importance of current vs. past behavior of an agent in determining its reputation. The notion of reputation is key in the game model, as it affects the probability of receiving service for a player, and forms the incentive mechanism to contribute service in the system. More detailed discussion is presented in Section IV.

B. Nash equilibrium of the game

In this section, we investigate the Nash equilibrium action profile of the service game defined above. Per the Nash Folk theorem, investigating this equilibrium for a single iteration of the game \(G\) will suffice, as \(G^\infty\) will have the same equilibrium [19]. The results of this section follow from the service game model, and as such, are based on [3].

In the game model, the utility that a player gains increases with the player’s contribution to the system, as the probability of receiving service is determined by the reputation of a player, which improves (increases) as the player provides service. Each player wants to gain the maximum benefit from the model, leading to a non-cooperative game. Nash equilibrium is reached when competition ends among the players. This occurs when the collective set of actions taken by the players with respect to service provision is locally optimum, i.e., no player can improve its utility by electing a different strategy. The two types of Nash equilibria are Pure and Mixed.

1) Pure Nash equilibrium: Pure Nash equilibrium results when every player declines to serve, i.e., elects the action \(\{Dcln\}\). This is easily proven. If only one player, \(i\), elects to serve, then its payoff is \(-C\), as compared to the (higher) payoff of 0 that would result from declining to serve. Every other player has declined to serve, and as such the serving player, \(i\), is unable to utilize its increased reputation to obtain service from others, discouraging further provision of service. This action profile leads to a stalemate, where no service is provided anywhere in the system, and as such is considered a trivial equilibrium.

The opposite case, where all players elect to serve is not a local optimum, and hence not a Nash equilibrium action profile. If every other player is providing service, then the best strategy for any single player is to decline service, resulting in a payoff of \(U\) instead of \(U - C\).

2) Mixed Nash equilibrium: The agents responsible for decision support in a WDN are considered to be peers, and members of a homogeneous population, in terms of capabilities and responsibilities. As such, it is assumed that the Nash equilibrium reached will be symmetric, i.e., all players will choose the same strategy. This enables us to drop the player index \(i\) in referring to parameters in the discussion below.

The symmetric equilibrium action profile of interest is mixed-strategy, where players elect to serve in some time periods and decline service in others. As previously mentioned, the pure-strategy equilibrium of no service throughout the system is not a sustainable operational state for a WDN.

In the mixed-strategy symmetric Nash equilibrium action profile, each player, \(i\), elects to serve with probability \(p\) and declines service with probability \(1 - p\), with \(p > 0\), meaning that either action is possible. We assume that each player can provide service prior to requesting it.

The expected payoff value of electing to serve during time period \(t\) is defined as:

\[
\text{Payoff}(Srv) = p \ast (-C + R(t, Srv) \ast U)
\]
In Equation 2, the term \((-C + R(t, Srv) \cdot U)\) illustrates the tradeoff inherent to service provision, namely, that cost of providing service as compared to the benefit of receiving service. The term \(R(t, Srv) \cdot U\) reiterates that the probability of obtaining service in the current time period depends on a player’s reputation. This payoff value of a player not only reflects its current payoff after providing service, but also captures the potential to obtain service in the next period, through the inclusion of \(R(t, Srv)\), which can be used as a health indicator that reflects the capability of the player to gain service in the near future. When service is provided, \(w = 1\), and per Equation 1:

\[
R(t, i) = R(t - 1, i) \cdot (1 - a) + a
\]

(3)

Similarly, the payoff value of selecting the action \(\{Dcln\}\) is:

\[
\text{Payoff}(Dcln) = (1 - p) \cdot (R(t, Dcln) \cdot U)
\]

(4)

The equation reflects the “no contribution, no cost” case. When service is declined, \(w = 0\), and per Equation 1:

\[
R(t, i) = R(t - 1, i) \cdot (1 - a)
\]

(5)

In a mixed-strategy Nash equilibrium of finite games, each player’s expected payoff should be the same for all actions. In other words, the respective payoff values for \(\{Srv\}\) and \(\{Dcln\}\) are equal:

\[
\text{Payoff}(Srv) = \text{Payoff}(Dcln)
\]

(6)

Substituting from Equations 2 and 4 yields:

\[
p \cdot (-C + R(t, Srv) \cdot U) = (1 - p) \cdot (R(t, Dcln) \cdot U)
\]

(7)

Incorporating the iterative definition of reputation, from Equations 3 and 5, the probability of service provision, \(p\), is determined as:

\[
p = \frac{R(t - 1) \cdot U(1 - a)}{-C + 2R(t - 1) \cdot U(1 - a) + Ua}
\]

(8)

Several noteworthy points arise from the equations above. Firstly, \(p\) changes during each time period, and is a function of the agent’s reputation at the end of the immediately preceding period, \(R(t - 1)\). Secondly, recall that this is a mixed-strategy Nash equilibrium action profile, where all players have the same \(p\). Thirdly, we contend that this equilibrium is more stable than the pure-strategy equilibrium discussed above, as self-interest will motivate agents to eventually provide service in order to increase their chances of receiving service.

IV. EXPERIMENTAL VALIDATION

A. Design of experiment

In this section, we present experimental validation of the game-theoretic approach to water allocation described in the previous two sections. Matlab simulation was implemented with the three interacting peer agents shown in Fig. 2.

The agents are labeled Node \(i\), Node \(j\), and Node \(k\), respectively. For each agent, the service strategy is as shown in Table I. The strategy shown in Table I does not exhaustively capture all actions that could be taken by the three agents, but it provides a representative set of actions over a non-trivial duration of ten time slots.

<table>
<thead>
<tr>
<th>Time (t)</th>
<th>Node (i)</th>
<th>Node (j)</th>
<th>Node (k)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Serve</td>
<td>Serve</td>
<td>Decline</td>
</tr>
<tr>
<td>2</td>
<td>Decline</td>
<td>Serve</td>
<td>Decline</td>
</tr>
<tr>
<td>3</td>
<td>Serve</td>
<td>Decline</td>
<td>Decline</td>
</tr>
<tr>
<td>4</td>
<td>Decline</td>
<td>Decline</td>
<td>Serve</td>
</tr>
<tr>
<td>5</td>
<td>Serve</td>
<td>Decline</td>
<td>Serve</td>
</tr>
<tr>
<td>6</td>
<td>Serve</td>
<td>Decline</td>
<td>Serve</td>
</tr>
<tr>
<td>7</td>
<td>Serve</td>
<td>Serve</td>
<td>Decline</td>
</tr>
<tr>
<td>8</td>
<td>Decline</td>
<td>Decline</td>
<td>Serve</td>
</tr>
<tr>
<td>9</td>
<td>Decline</td>
<td>Decline</td>
<td>Serve</td>
</tr>
<tr>
<td>10</td>
<td>Serve</td>
<td>Serve</td>
<td>Decline</td>
</tr>
</tbody>
</table>

According to the Table I, we can summarize the strategy of each player, \(i\), as \(W_i\) below:

- \(W_i = [1001011001]\)
- \(W_j = [1100001001]\)
- \(W_k = [0001110010]\)

The configuration of initial values for the utility of obtaining service \(U\) and the cost of providing service \(C\) is \(U/C = 80\), with \(U = 800\) and \(C = 10\). The main reason to adopt the ratio of utility to cost, \(U/C = 80\), rather than their difference, \(U - C\), is the normalization inherent to use of the ratio. In civil engineering literature, water pricing has been approached from a supply and demand perspective [20], [21], which is what \(U\) and \(C\) try to capture.

The \(U/C\) ratio can reflect whether the water resource is scarce or sufficient. \(U/C\) is low when water is scarce, as serving a limited resource to other agents while maintaining sufficient resources for own usage purpose will be expensive for an agent, leading to high \(C\); and gaining utility from other agents is difficult, leading to low \(U\). Similarly, \(U/C\) is high when sufficient water exists for all peer agents. Our initial choice of \(U/C = 80\) for the simulation reflects a non-draining situation. Simulation results for other values of \(U/C\) are presented in subsection IV-B.

B. Discussion of results

1) Agent reputation over time: Firstly, based on the service strategy, we investigate how an agent’s reputation varies in the 10 time slots by following the equilibrium strategy described in Section III. Fig. 3 depicts the changes in \(R(t)\) for each of the three agents.
According to the strategies $W_i$, $W_j$, and $W_k$, respectively, the results show that the reputation value increases when the service is provided by a particular agent and decreases when the agent provides no service at all (or accepts service from its peers). The equilibrium strategy maintains the stability that over the 10 time intervals, the three peer agents’ action, i.e., providing service or accepting service, will be similar to each other. None agent can be constantly acquiring service or contribute service.

2) Probability of service provision over time: Secondly, we investigate how the probability of service provision varies over time. Simulation results are shown in Fig. 4.

According to Equation 8, $p$ varies in each time interval depending on the agent’s reputation at the end of the previous time interval. As $U$, $C$ and $a$ remain constant in this scenario, the agent’s reputation at the end of the previous time interval is determined by its strategy, $W$. If during the previous time interval, the agent provided service, then in the next time interval, the probability of service provision by the agent increases. If the agent did not provide service in the previous time interval, then the probability of providing service decreases.

Another observation is that if an agent continuously provides service to its peers, then the increase in probability of service provision within each interval, compared with the previous interval, will actually decrease (indicated as the circle in the figure for player $k$). This again demonstrates the role of the equilibrium strategy in the resource allocation (service provision or receipt), i.e., to restrain an agent that is constantly providing or constantly obtaining service.

3) Steady-state behavior: An interesting question is whether steady-state behavior of the water allocation game will settle on a service provision probability, $p$, of 0.5. Figs. 5 through 10 provide valuable insight.

Fig. 5 illustrates the case for player $i$, where $U/C = 80$, $a = 0.2$, and the strategy for 100 time slots consists of repeating $[1 0 1 0 1 1 0 0 1] [1 1 0 0 0 0 1 0 0 1] [0 0 0 1 1 1 0 0 1 0]$. The maximum value reached by $p$ is 0.45.

Keeping $U/C = 80$, $a = 0.2$, but changing the strategy of agent $i$ to 100 time slots of repeating $[1 0 1 0 1 1 1 0 0 1]$, the simulation result is as depicted in Fig. 6. Similar to the case above, $p$ barely reaches 0.45.

In the third test case, we still have $U/C = 80$ and $a = 0.2$, but the strategy of agent $i$ remains a constant 1 over 80% of the simulation time, which means that agent $i$ is serving most of the time. The simulation result shown in Fig. 7 illustrates that $p$ still does not reach 0.5.

In yet another experiment, we maintained $U/C = 80$, but changed $a$ to 0.01, corresponding to a system with a good memory (past actions of a player have strong bearing over its reputation). With near-continuous service provision, the simulation results were as depicted in Fig. 9, where unlike the aforementioned cases, $p$ reaches 0.5. Considering the factors that can affect $p$ in equation 8, we investigated the situation if $U/C$ ratio is changed to 8 and $a$ remains the same, the simulation result in Fig. 8 shows that $p$ can reach 0.5.
Finally, we investigate the case that the agent is continually requesting service in the beginning, i.e., $W$ is 1 for the first third of the simulation time. The simulation results are depicted in Fig. 10. Simulation results show that regardless of variations in $U/C$ and service strategy, when time goes to infinity, the value of $p$ is mainly determined by the constant $a$, which reflects the importance of serving during the current period.

4) Reputation vs. service behavior: In addition to the probability of service provision, $p$, we also investigate how the agent reputation, $R(t)$, changes with variations in the strategy, $W$. Simulation results are shown in Fig. 11, which illustrates that the collaborative decision making strategy discourages continual provision of service by an agent.

5) Reputation vs. memory: For additional insight into the effect of various parameters on the system operation, we vary $a$ to be 0.2, 0.4, 0.6 and 0.8, respectively to see how the reputation changes as $a$ changes. Fig. 12 shows the variations in the reputation of agent $i$ for different values of $a$. The same strategy, $W = [1010111001]$, is used for the four groups of data.

As seen in Fig. 12, a larger $a$ will cause a more drastic change in the reputation during each time interval. This
is because the constant \( a \) plays a major role in terms of deciding the importance of service provision in determining the reputation, \( R(t, i) \), of an agent (see Equation 1).

From the above analysis, it is clear that the role played by \( a \) is encouraging instability in the system, akin to genetic mutation. The instability can bring some benefits to the system. In the biochemical pollutant case, instability can be used to flush out the biochemical pollutant quickly; or in the social network case, instability can help to quickly extend the social network. Evolutionary game theory offers explicit dynamics to introduce a strategic aspect to evolution [22]. A related discussion is beyond the scope of this paper.

6) Accumulated payoff vs. service behavior: The simulation results depicted in Figs. 13 to 16 show that the accumulated payoff values for \( \{Srv\} \) and \( \{Dcln\} \), respectively are quite close, regardless of changes in \( a \). The service ratio, defined as ratio of the accumulated payoff value for \( \{Srv\} \) to the accumulated payoff value for \( \{Dcln\} \), is 1.07, 0.95, 0.84 and 0.74, respectively, for \( a = 0.2, 0.4, 0.6, \) and 0.8.

As depicted in Fig. 17, the variation in service ratio decreases as \( a \) increases.

As seen in Equation 1, as \( a \) increases, an agent’s reputation in the previous time interval plays a less important role in determining the agent’s current reputation, i.e., the system’s memory becomes weaker. As an agent’s reputation increases only when it provides service to its peers, an increased \( a \) can discourage the agent from contributing service to the system, and hence lead to a decrease in the \( \{Srv\}/\{Dcln\} \) ratio.

7) Accumulated payoff vs. \( U/C \): We also investigate how the payoff value varies as \( U/C \) varies. Figs. 18 through 22 illustrate the payoff value for each time period, for different \( U/C \) ratios.

The simulation results are summarized in Table. II. The variation of \( U/C \) from 8 to 80 leads to very little change in the service ratio, \( \{Srv\}/\{Dcln\} \); however, when \( U \) and \( C \) are nearly equal, as in they are in Fig. 18, the payoff value, and hence the service ratio may become negative. If \( U/C = 1 \), the payoff value explodes to \( \infty \).

8) Service probability and payoff vs. \( U/C \): Finally, we investigate the effect of \( U/C \) on the probability of service provision and the payoff. Fig. 23 depicts the probability of service provision for values of \( U/C \) ranging from 40 to 120.
Fig. 24 provides a more detailed view of the same simulation results.

Dividing the numerator and denominator of Equation 8 by $C$ yields:

$$p = \frac{R(t-1) \cdot (U/C)(1-a)}{(-1 + 2R(t-1) \cdot (U/C)(1-a) + (U/C)a} \quad (9)$$

Fig. 24 illustrates that the lower the $U/C$ ratio, the higher the probability of service provision. With a low $U/C$ ratio, an agent will achieve a lower payoff value if it obtains service, as compared to the alternative action of providing service. Therefore, a lower $U/C$ ratio can encourage agents to provide service rather than obtain or decline service. However, the impact of $U/C$ on the probability of service provision appears...
TABLE II
SERVICE RATIO FOR DIFFERENT U/C VALUES.

<table>
<thead>
<tr>
<th>U/C</th>
<th>Service ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>-1.27</td>
</tr>
<tr>
<td>8</td>
<td>0.89</td>
</tr>
<tr>
<td>20</td>
<td>0.89</td>
</tr>
<tr>
<td>40</td>
<td>0.89</td>
</tr>
<tr>
<td>80</td>
<td>0.89</td>
</tr>
</tbody>
</table>

to be quite minor.

Fig. 25 depicts the effect of $U/C$ on the payoff value. As seen in the figure, the higher the $U/C$ ratio, the higher the payoff value will be within each time interval. According to the expected payoff function for an agent in time period $t$, if an agent provides service, the payoff value will be negative. The strategy represented is $W = [1010111001]$. As depicted in the center area of the figure, service provision can help to increase the payoff value.

The work presented in this paper employs a cyber-physical perspective towards environmental decision support, in the context of intelligent water distribution. An agent-based EDSS was presented that utilized game theory for allocation of water among consuming entities. Simulation was used to validate the model, and experimental results were discussed at length, shedding light on the role of factors such as system memory and service provision strategies in water distribution.

The modeling and simulation presented in this paper is a first step that will facilitate further research towards CPS-based environmental decision support and management. The results can be generalized to other infrastructure systems, such as smart grids. Future extensions to this work will involve refinements to the game-theoretic algorithm, incorporation of sensor data into the decision support, and investigation of service-oriented computing for facilitation of the complex computations required.

REFERENCES

Agent 1:
Attributes 1:
\[
\begin{align*}
\text{string actions} &= \{\text{serve}, \text{decline}\}; \\
\text{int time interval } t &= 0; \\
\text{int utility value } U &= 0; //U \text{ can be initialized as 800} \\
\text{int cost value } C &= 10; //C \text{ can be initialized as 10} \\
\text{double reputation of the node } R &= 0.5; //R \text{ is constrained to } (0,1) \\
\text{double parameter } a &= 0.2; //a \text{ is constrained to } (0,1) \\
\text{double payoff}[\text{serve}] &= \text{payoff}[\text{decline}] = 0; \\
\end{align*}
\]

Methods 1:
\[
\begin{align*}
\text{(for } t = 1; \ t <= 10; \ t++ \text{)} \\
&\text{Receive request from agent 2 } \{\text{serve2} = 1\}; //\text{store the } \{\text{serve}\} \text{ request from} \\
&\text{Receive request from agent 3 } \{\text{serve3} = 1\}; //\text{different agents for further service provision} \\
&\text{Provide service to agent 2 }; \\
&\text{Provide service to agent 3 }; \\
&\text{Increment own reputation (double R)} \\
&\quad R(t) = R(t-1)*(1-a)+w*a; //\text{store the current reputation value for further computing} \\
&\text{Calculate service probability } p \text{ for next time interval (double p)} \\
&\quad p = (R(t-1)\times U*(1-a))/(C+R(t-1)\times U*(1-a)+U*a) \\
&\text{Calculate payoff value (double payoff)} \\
&\quad \text{if } \{\text{serve}\} = 1 \text{ then } // \text{case that agent 1 serves other agents} \\
&\quad \quad \text{payoff}[\text{serve}] = p*(-C+R(t)\times U); \text{return } \text{payoff}[\text{serve}] \\
&\quad \quad \text{else then } // \text{case that agent 1 declines to serve} \\
&\quad \quad \quad \text{payoff[decline]} = (1-p)\times (R(t)\times U); \text{return } \text{payoff[decline]} \\
\end{align*}
\]

Fig. 27. C++ code for Agent 1.


