CoopRA Algorithm for Universal Characterization of the Experimental Evaluation Results of Cooperative Multiagent Systems

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Abstract

Experimental evaluation of the cooperative multiagent systems (CMASs) provides an assessment way that should be analysed. In this paper, we propose an algorithm with acronym *CoopRA* that can make a deep performance characterization, based on different indicators, of the experimental evaluation results of a CMAS. This could lead to the formulation of helpful information in some decisions related to the performance of the studied CMASs. In order to validate the proposed algorithm, we performed a case study on a CMAS composed of simple reactive agents that operate by mimicking the problem/task solving of natural ants. We chose this type of cooperative multiagent system architecture, based on the fact that even in case of the cooperative multiagent systems composed of simple efficiently and flexibly cooperating agents could emerges an increased problem solving intelligence at the system's level. The evaluation was performed for the Travelling Salesman Problem (TSP) solving that is a well-known NP-hard problem, having many real-life applications.

Keywords: intelligent system, cooperative multiagent system, NP-hard problem, travelling salesman problem, nature inspired computing, ant colony optimization, digital image processing, medical imaging.

1. Introduction

Cooperative multiagent systems (CMASs) represent a subclass of the agent-based systems. By cooperating efficiently and flexible, even in CMASs composed of simple agents could emerge an increased problem-solving performance that could result even in intelligence. Frequently, developed cooperative multiagent systems are considered intelligent based on the extremely performant problem-solving ability (Iantovics & Zamfirescu, 2013; Yang et al., 2003). Many real-life difficult problem-solving is based on CMASs (Beni & Wang, 1993; Mir, Merghem-Boulahia & Gaïti 2009; Hao et al., 2017; Zamfirescu & Filip, 2010; Bouzouita, Chaari & Tagina, 2017; Khalil et al., 2015; Pătruţ, 2014; Arif et al., 2015; Filip & Leiviskä, 2009). There are different types of computational problems, which could be described by data, signals or images. Different kind of difficulties related to the image processing are treated in the papers (Kountchev & Kountcheva, 2017; Georgieva, Kountchev & Draganov, 2014; Georgieva & Draganov, 2016). There are many approaches to image processing based on intelligent agent-based systems such as different medical image segmentation (see for example Bensag, Youssfi & Bouattane, 2015). Agent-based systems require often the treating of different security-related aspects. The papers and books (Iantovics, 2015; Kerti & Nyikes, 2015; Nyikes, Németh & Kerti, 2016; Albini & Rajnai, 2018; Peng et al., 2018; Flammini et al. 2009; Flammini, 2018) treats a variety of aspects and propose some solutions related to the security in different systems including agent-based systems.

For the analysis of cooperative multiagent systems experimental evaluation results, usually, there are performed some traditional calculus like, for example, the average problem-solving time; in case of the TSP, the average length of the tour found in more consecutive running of the algorithm. There are several papers that propose some specific approaches related to different aspects of performance evaluation.

Gordillo and Giret (2014) studied some specific CMASs applied in manufacturing that use algorithms for task allocation. The main contribution consists in the proposal of a mechanism to measure the performance of agent-based scheduling approaches for manufacturing systems.

Ajitha and collaborators (Ajitha et al., 2012) performed an analysis of the performance of software systems. Software performance engineering is important in order to describe the performance of systems at the development stage. It is proposed a methodology to predict the performance of CMASs based on an approach that considers the importance of cooperative behaviour of the agents. In the proposal, a designed mathematical model and the Unified Modeling Language diagrams are used to give a quantitative measure to the cooperation of the agents.

Dimou and collaborators (Dimou et al., 2015) outlined the lack of generalized methodologies for assessing the performance of agent-based systems. The authors consider that existing methods do not adequately address the complex nature of many systems. It is proposed a generic methodology for evaluating the performance of agent-based systems.

We consider that on obtained experimental evaluations results can be performed some specific analysis that allows the formulation of different kind of useful conclusions related to the performance of studied CMAS operation. As examples, we mention: the verification of the experimental evaluation results normality, the verification of the experimental evaluation results homogeneity/heterogeneity and the spreading of the experimental evaluation results across the mean. In this paper, we propose a more complete analysis and characterization of the cooperative multiagent systems experimental evaluation based on an algorithm called *Characterization of the Experimental Evaluation Results* (*CoopRA*).

For the validation of the proposed algorithm, we present a case study in which a CMAS composed of simple reactive agents that operates like a colony of natural ants solves an NP-hard problem. It was selected this type of CMAS based on the fact that even very simple efficiently and flexible cooperating agents could have at the group/coalition or multiagent systems level an increased intelligence. It was selected a specific type of problem the well-known *Travelling Salesman Problem* (TSP) for the case study based on the consideration that is an NP-hard problem, which computationally is extremely difficult. A very large effort is put on the TSP solving. It have numerous real-life applications. Our proposed *CoopRA* algorithm is universal, it is not restricted to *CMASs* by the type of operation presented in the case study (is not dependent on the CMASs architecture, and the composing agents architecture) and is not restricted to CMASs that solve the type of problem that is solved in the case study.

The upcoming part of the paper is organized as follows: in Section 2 is presented the proposed *CoopRA* algorithm for characterization of the experimental evaluation results of a CMAS; Section 3 presents the performed case study, in Subsection 3.1 is presented the solved NP-hard problem, Section 3.2 presents the general operation of CMASs that operates like colonies of natural ants, in Subsection 3.3 the operation of the studied CMAS is presented, there are presented and discussed the obtained experimental evaluation results and Section 4 presents the conclusions of the paper.

2. CoopRA proposed algorithm for experimental evaluation results analysis

We denote with *IC* a cooperative multiagent system composed of a set of agents denoted Ag_1, Ag_2,…,Ag_n; $IC=\{Ag_1, Ag_2,\ldots,Ag_n\}$. $|IC|$, $|IC|=n$ represents the number of agents that compose *IC*. We consider the experimental evaluation of the *IC* system on a problem set denoted $Probl=\{Prl_1, Prl_2,\ldots, Prl_k\}$. $|Probl|$, $|Probl|=k$ denotes the number of problems used in the experimental evaluation. The obtained experimental evaluation results (solving of the problems *Probl*) are denoted as $Exp=\{Exp_1, Exp_2,\ldots, Exp_k\}$. Where: Exp_1 denotes the obtained solution by solving Prl_1; Exp_2 denotes the obtained solution by solving Prl_2;…; Exp_k denotes the obtained solution by solving Prl_k. Figure 1 presents the main processing steps performed by the *CoopRA* algorithm. This is followed by the presentation of the *CoopRA* algorithm in details.

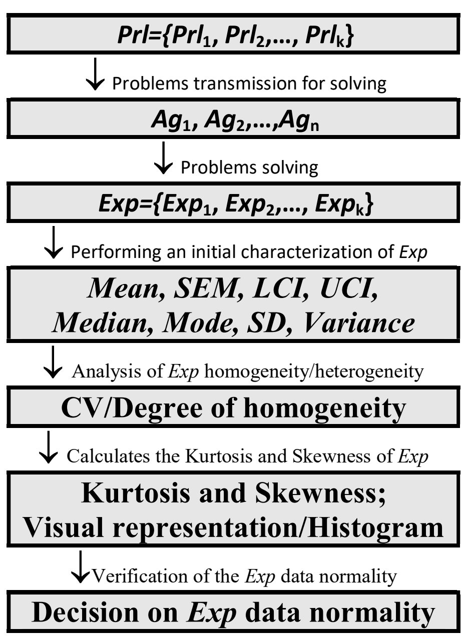

Figure 1. The processing performed by the CoopRA algorithm

In the following, we discuss all the proposed indicators of the experimental evaluation results presented in the *CoopRA* algorithm and explain their meaning.

K represents the number of solved problems used in the experimental evaluation. *Mean* represents the mean of the experimental evaluation results. The *Standard Error* (*SE*) of a parameter is the standard deviation of its sampling distribution. If the parameter or the statistic is the mean, it is called the standard error of the mean. *SEM* denotes the *Standard Error of the Mean*. *CL* denotes the *Confidence Level of the Mean*, we recommend the use of 95% in most of the cases. *LCI* denotes the *Lower Confidence Interval of the Mean. UCI* denotes the *Upper Confidence Interval of the Mean*. Both *LCI* and *UCI* are calculated at the established *CL* level.

Median represents the median of the experimental evaluation results. *SD* denotes the *Standard Deviation* of the experimental evaluation results. *SD* value expresses the quantity by how much the members of a group differ from the mean of the group. *SD* quantifies the amount of variation or dispersion of a set of data values (Bland & Altman, 1996). *Variance* denotes the variance. The *variance* measures how far a set of numbers are spread out from their average value. *Min* denotes the smallest value. *Max* denotes the largest value. *Range* is calculated as the difference between *Max* and *Min*; *Range=Max-Min. Mode* represents the most frequent experimental evaluation result.

```
CoopRA: Characterization of the Experimental Evaluation Results Algorithm
IN:IC={Ag1, Ag2,…,Agn}; Probl={Prl1, Prl2,…, Prlk}.
Out: //Indicators of the characterization
Mean, SEM, LCI, UCI, Median, Mode, SD, CV, Variance.
Step 1: Obtaining of the experimental evaluation results.
Exp:={Exp1, Exp2,…, Expk}.//Results of the Probl solving.
Step 2: Performing an initial characterization.
K:=|Exp|. Mode:=Mode(Exp1, Exp2,…, Expk);
Median:=Median(Exp1, Exp2,…, Expk); Mean:=Mean(Exp1, Exp2,…, Expk);
SEM:= SEM(Mean);
CL:=95%;//Set the CL value, we recommend the 95%.
@Calculates LCI, UCI.
SD:=SD(Exp1, Exp2,…, Expk); Variance:=SD^2;
Min:=Min(Exp1, Exp2,…, Expk); Max:=Max(Exp1, Exp2,…, Expk); Range:= Max-Min;
Step 3: Analysis of homogeneity/relative homogeneity/heterogeneity.
CV:=100×(SD/Mean);
If (CV∈[0,10)) Then
  "Exp is homogeneous;"
  ElseIf (CV∈[10, 30)) Then
   "Exp is relative homogeneous."
     Else //CV≥30
     "Exp is heterogeneous."
EndIf
Step 4: Calculates the Kurtosis and Skewness.
Skewness:=Skewness(Exp1, Exp2,…, Expk); Kurtosis:= Kurtosis(Exp1, Exp2,…, Expk);
@Construct the histogram for the visual interpretation of Kurtosis and Skewness;
Step 5: Verification of the Exp data normality.
α:=0.05; //Set the significance level of the normality test.
//Formulates the hypothesis of the normality test.
//H0 the null hypothesis and H1 the alternative hypothesis.
@Formulates H0 and H1;
@Verify the Data Normality using the KS-test;
//Let Pks the obtained KS-test result.
If (Pks>α) Then
   @Accept H0;
   "Exp is normally distributed".
   Else
     @Accept H1;
     "Exp is NOT normally distributed."
Endif
EndCoopRA
```

Skewness (Joanes & Gill, 1998) is a measure of lack of symmetry. A dataset is symmetric if it looks the same to the left and right of the center point. Figure 2 ilustrates the graphical representation of *Skewness,* with Figure 2(a) illustrating the negative *Skewness,* and Figure 2(b) illustrating the positive *Skewness.*

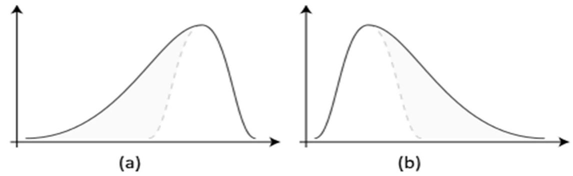

Figure 2. Graphical representation of the Skewness: (a) Negative skewness and (b) Positive skewness.

Kurtosis (Joanes & Gill, 1998) can be defined as the measure of whether the data are light-tailed or heavy-tailed relative to a normal distribution. Figure 3 graphically presents the significance of *Kurtosis*. Data sets with high kurtosis tend to have heavy tails (outliers). Data sets with low kurtosis tend to have light tails (lack of outliers).

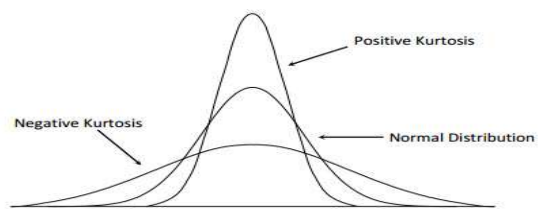

Figure 3. Graphical representation of the kurtosis.

It is useful to be considered the histogram as a very useful graphical technique for visual interpretation (Pearson, 1895). The humans and computing systems have different strengths and weakness comparatively with each other. From human point of view, easier versus the computing systems is the taking of some decisions based on visual interpretation. Among others, a histogram is useful for showing the skewness and kurtosis of a studied experimental evaluation data set.

The *Coefficient of Variation* (*CV*) (Everitt, 1998) if is expressed in percentage (%) is calculated as $CV=100\times(SD/Mean)$. The coefficient of variation is appropriate for the analysing the homogeneity/relative-homogeneity/heterogeneity of the experimental evaluation results. It can be considered the characterization of homogeneity/heterogeneity based on the *CV* value as follows: if $CV\in[0\%, 10\%)$ we call the experimental evaluation data homogeneous; if $CV\in[10\%, 30\%)$ we call the experimental evaluation data relative homogeneous; if $CV\geq 30\%$ we call the experimental evaluation data heterogeneous.

In step 5 of the *CoopRA* algorithm, is described the verification of the *Exp* data normality. More specifically, it is verified if the *Exp* is sampled from a Gaussian population. This information allows the formulation of some conclusions. For this verification, we used the *One-Sample Kolmogorov-Smirnov test* (*KS-test*) (Massey, 1951; Miller, 1956; Marsaglia, Tsang & Wang, 2003) that is one of the most frequently used statistical tests in the verification of the normality. The *KS-test* should be applied at an established significance level that we denote with α. In statistical hypothesis testing, a type I error is the incorrect rejection of a true null hypothesis. In other words, this could be called as a "false positive" finding. Concretely α denotes the probability to make a type one error. We recommend in most of the cases the application of the KS-test at the $\alpha=0.05$ significance level.

We denote with *H0* the Null Hypothesis, which confirm that the *Exp* dataset is normally distributed. We denote with *H1* the Alternative Hypothesis, which confirms that the *Exp* dataset is NOT normally distributed. The P-value of the KS-test is denoted in the algorithm with *Pks*. If $Pks>\alpha$ than can be concluded that H0 can be accepted, having the significance that the normality test passed. Elsewhere if $Pks \le \alpha$, H0 must be rejected and H1 should be accepted, the passing of the normality assumption being failed.

3. The performed case study

3.1. Travelling Salesman Problem definition

Travelling Salesman Problem (*TSP*) was formulated in the 1800s by William Hamilton and Thomas Kirkman. *TSP* can be enounced as follows (Dorigo, 1997; Bernardino & Paias, 2018; Bao, Liu, Yu, & Li, 2017): given *M* nodes (cities) that form a directed graph, a salesman starts from a given node, he/she must visit each node exactly once and then return to the starting position (node). The salesman would like to choose the route that minimizes the total travelled distance. *TSP* is one of the most well-known NP-hard problems. Given *n* the number of cities to be visited, the total number of possible routes covering all cities can be given as a set of feasible solutions of the *TSP* calculated as (n-1)!/2.

The *TSP* has several real-life applications, like: drilling of printed circuit boards (Grötschel, Jünger & Reinelt, 1991), overhauling gas turbine engines (Plante, Lowe, & Chandrasekaran, 1987), X-Ray crystallography (Bland & Shallcross, 1989), computer wiring (Lenstra, & Rinnooy Kan, 1974), and vehicle routing (Ratliff & Rosenthal, 1983).

3.2. CMASs that operate like natural ants

Dorigo (Dorigo, Maniezzo, & Colorni, 1991; Colorni, Dorigo, & Maniezzo, 1991; Dorigo, 1992) proposed first the problem-solving based on simple computing agents that mimic the behavior of natural ants in searching for food. In an *Ant System* (*AS*), initially, each agent (artificial ant) is placed on some randomly chosen node of the graph. A node represents a city in case of the *TSP*. An agent *k* currently at node *i* chooses to move to node *j* by applying the following probabilistic transition rule:

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{[\tau_{ij}(t)]^{\alpha}\cdot[\eta_{ij}]^{\beta}}{\sum\limits_{l\in J_k(i)}[\tau_{il}(t)]^{\alpha}\cdot[\eta_{il}]^{\beta}} & \text{if } j\in J_k(i)\\ 0 & \text{otherwise}\end{cases} \tag{1}$$

After each agent completes its tour, the pheromone amount on each path will be adjusted as follows:

$$\tau_{ij}(t+1)=(1-\rho)\times\tau_{ij}(t)+\Delta\tau_{ij}(t) \tag{2}$$

$$\Delta\tau_{ij}(t)=\sum_{k=1}^{k=m}\Delta\tau_{ij}^{k}(t) \tag{3}$$

$$\Delta\tau_{ij}^{k}(t)=\begin{cases}\dfrac{Q}{L_k} & \text{if (i,j)}\in tour\_performed\_by\_agent\_k\\ 0 & \text{otherwise}\end{cases} \tag{4}$$

ρ, α, and β are adjustable parameters. ρ is the evaporation factor. In different implementations, ρ value $\rho\in(0,1)$. α and β control the relative weights of the heuristic visibility and the pheromone trail. *Q* denotes an arbitrary constant. Very frequently *Q* value is set to *1*. $d_{r,z}$ represents the distance between the nodes *r* and *z*. η_{rz} ($\eta_{rz}=1/d_{r,z}$) stands for the heuristic visibility of the edge (*r*,*z*). The number of agents is denoted by *m*. L_w stands for the length of the tour performed by the agent *w* ($w\in$[1,m]).

The agents' members of such a studied system have a reactive architecture. They operate in an environment represented by a graph of connected nodes. They are able to move in the environment from node to node during a problem-solving. Many of the multiagent systems that operate by mimicking the natural ants are considered intelligent in the scientific literature. They are considered to have what can be called as *Swarm Intelligence* (*SI*). The expression of *SI* was introduced by Gerardo Beni and Jing Wang (Beni & Wang, 1993). There are many studies (see for example Chatterjee et al., 2017) focused on problem-solving using different types of swarm systems. The intelligence of cooperative multiagent systems that mimic by their operation the natural ants, frequently, is considered based on the analogy to the intelligence level at the colony of natural ants and the ability of very difficult problem solving (for example, there is solved an NP-hard problem). Figure 4 illustrates an intelligent task solving by some ants.

Figure 4. Intelligent cooperative natural ants [http://sciencenordic.com/ants-make-medicine-out-tree-sap-and-fungi accessed on 27.03.2018]

3.3. Operation of the studied CMAS

The first modified version of the *AS* consisted in the *Ant Colony System (ACS)*. The *Ant Colony System* was introduced by Dorigo and Gambardella (1997). *Min-max Ant System (MMAS)* was proposed by Stützle and Hoos (2000). *MMAS* was applied for different real-life problems solving (Stützle & Hoos 2000; Prakasam & Savarimuthu, 2016).

There are developed different applications of *MMAS* for different real-life problems solving (Stützle & Hoos 2000; Prakasam & Savarimuthu, 2016).

IC used in this case study operated similarly as a *MMAS*. *MMAS* differs from the conventional *AS* based on different points of view. An *MMAS* give dynamically evolving bounds on the pheromone trail intensities. The pheromone intensity on all the paths is always within a specified limit of the path with the greatest pheromone intensity. All the possible paths have permanently a non-trivial probability of being selected. This approach allows a wider exploration of the search space. There are used lower and upper pheromone bounds to ensure that all of the pheromone intensities are between these two bounds. The solution construction is according to (1). There are minimal and maximal pheromone limits to the quantity of pheromone on the paths between nodes, denoted as τ_{min} and τ_{max}. The evaporation is expressed as (5). Equation (6) denotes the pheromone update based on the selected agent's round trip.

$$\tau_{ij}(t) = \max((1-\rho)\times\tau_{ij}(t), \tau_{\min}) \tag{5}$$

$$\tau_{ij}(t+1) = \min(\tau_{ij}(t) + \Delta\tau_{ij}^{bs}(t), \tau_{\max}) \tag{6}$$

There are used the following notations. $\Delta\tau_{ij}^{bs}(t)=Q/L^{sel}$ if the path $ij \in T^{sel}$, T^{sel} is the selected best to date agent's round trip, L^{sel} is the length of the performed trip. In the performed experiments we have initialized $\tau_0=1/NumberOfCities$. As another possibility for τ_0 initialization that could be applied we mention $\tau_0=\tau_{max}$. The most appropriate approach for initialization could not be calculated theoretically, it must be established experimentally.

3.4. The performed experimental evaluation

There were performed 18 experimental evaluations, $Probl=\{Prl_1, Prl_2,\ldots, Prl_{18}\}$, using a computing system with I7-4720HQ processor and 8 GB Ram memory. It was considered the *TSP* solving with *NumberOfCities*=90. The parameters values were established experimentally, as follows: *MaxTests*(*NumberEpochs*)=50, α=1.6, β=1.5, ρ=0.28, *m*=10.

Figure 5 illustrates graphically the obtained experimental evaluation results. Table 1 depicts the obtained experimental evaluation results. Figure 6 shows graphically the epochs in case of each problem-solving when is obtained the global-best solution during the search for the problem-solution.

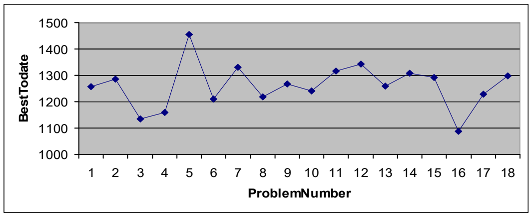

Figure 5. The obtained experimental evaluation data

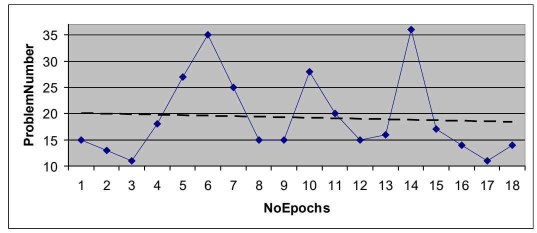

Figure 6. Number of epochs for the obtaining of the solution

Table 1. The obtained experimental evaluation data

BestToDate	***Epoch***	***BestToDate***	***Epoch***
1257	15	*1241*	28
1286	13	*1317*	20
1134	11	*1342*	15
1159	18	*1260*	16
1456	27	*1309*	36
1211	35	*1291*	17
1330	25	*1088*	14
1218	15	*1228*	11
1268	15	*1298*	14

Table 2 presents the results obtained by applying the proposed *CoopRA* algorithm. The *mode* value has not been obtained based on the fact that each experimental evaluation value appeared a single time. Figure 7 represents the histogram created based on the best-to-date-data. Among others, it was created in order to make a visual appreciation of the *Kurtosis* and *Skewness.*

Table 2. Results obtained by applying CoopRA

Indicator	***Value***
Median/Mode	1264/NA
SD/Variance	84.03/7061.5
Mean/SEM	1260.72/19.8
CL, [LCI, UCI]	95%, [1218.9, 1302.5]
CV/CV interpretation	6.67/Homogeneose
Kurtosis/Skewness	1.1/0.02
Min/Max/Range/Count	1088/1456/368/18

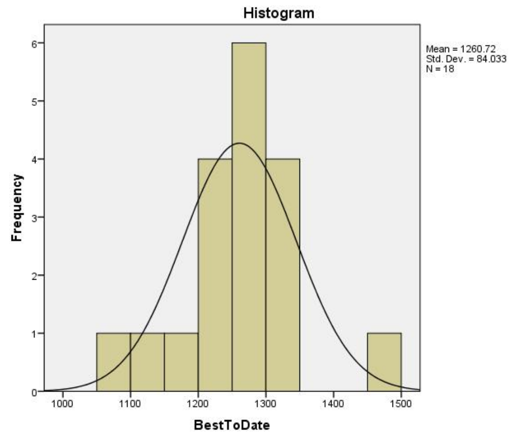

Figure 7. Histogram of the BestToDate

For the appreciation of the data normality, we considered the visual interpretation of Figure 7 and the interpretation of the *KS-test* result. It was considered the application of the *KS-test* at the α=0.05 significance level. For the KS-test result, it was obtained the value of *KS*=0.1112 and the *Pks*>0.1 (P value of the KS-test). According to step 5 of the algorithm, based on the fact that *Pks*>α, can be concluded that *H0* can be accepted. This has the meaning that *Exp* is normally distributed. The obtained *CV* value was 6.67, according to the Step 3 of the algorithm, *CV*<10 indicating a homogeneous experimental evaluation data.

4. Conclusions

Cooperative multiagent systems, in many cases, outperform other systems, like the agents that operate individually, in different computational hard problems solving. Based on this fact they can be successfully applied for a large variety of real-life problems solving. Difficulties in the computing problem solving could appear based on fact that they are NP-hard, solving encounter different types of challenges such as: incomplete description, the description contains erroneous data, etc.

In case of experimental evaluation of many cooperative multiagent systems, there are missed some calculus that could allow the formulation of different useful conclusions related to the performance. Based on this motivation, we propose an algorithm called *Characterization of the Experimental Evaluation Results* (*CoopRA*). Our proposal is useful for a deeper analysis of the cooperative multiagent systems experimental evaluation results than other approaches. This analysis could lead to the possibility of a formulation of more accurate decisions related to the problem-solving performance mostly in case of CMAS that have a heuristic problem-solving behaviour. For example, we mention a swarm of mobile robotic agents specialized in exploring an unknown place of environment. Different runnings on the same problem solving could lead to different experimental evaluation results.

For the validation of the *CoopRA* algorithm, we performed an illustrative experimental case study. It was considered the Travelling Salesman Problem solving by a cooperative multiagent system composed of simple reactive agents that mimic the operation of natural ants in search of food. *TSP* is one of the most intensely studied NP-hard problems, which has applications for many real-life problems solving.

The proposed algorithm for characterization of a CMAS is universal. It is not restricted to a specific type of cooperating multiagent system, or a specific type of problem-solving. As examples of possible applications we mention: cooperative robotic agents specialized in collecting objects in the environment or cooperative swarms of agent-based drones specialized in delivering goods to clients.

The future works will consist in the study if this characterization could be extended in order to make a deeper characterization of the experimental evaluation results such that it allows performing more precise characterization of a CMAS performance. One of the studied direction will consists in the analysing of the possibility to make a characterization of the central performance tendency. For this purpose, we intend to design an algorithm that will be based on some specific calculus.

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