A Game Theory Model for Multi Robot Cooperation in Industry 4.0 Scenarios

Elvina Gindullina, Eleonora Peagno, Giovanni Peron, and Leonardo Badia
Dept. of Information Engineering (DEI), University of Padova, Italy
email: elvina.gindullina@unipd.it, {eleonora.peagno,giovanni.peron}@studenti.unipd.it, leonardo.badia@unipd.it

***Abstract*—Multiple autonomous robots are expected to interact in Industry 4.0 scenarios, which makes it key to identify distributed techniques for their control and coordination. Game theory has a strong potential to be an excellent representation methodology for the establishment of cooperation among distributed robotic agents. In this paper, we consider a model of two industrial robots within a production line and we show how to describe their interaction, with their different objectives and control being kept into account. We also formalize a Bayesian game that takes into account imperfections in the system, such as the possibility that the robots make a wrong evaluation on a specific item in production. For both the standard static game and its Bayesian version, we compute the Nash equilibrium and we argue how it ultimately represents a point of convergence of the distributed control of the robots.**

***Index Terms*—Game theory; Industrial control; Mathematical modeling; Robotic assembly.**

I. Introduction

Since its earliest origin, distributed robotics has been expanding to a variety of applications in real-world scenarios, and is nowadays envisioned as an enabler of new functionalities in health technologies, smart agriculture, surveillance and disaster management, and many other fields [1], [2]. In particular, we consider the applications of distributed robotics towards the fourth industrial revolution, also dubbed as Industry 4.0, i.e., a trend in manufacturing technologies that expected to leverage cyber-physical systems and the Internet of things to achieve unmanned operation and efficient production to an unprecedented level [3].

According to the influential reference of [4], autonomous robots make one of the nine pillars of Industry 4.0. Indeed, they can be used for many crucial applications such as structural monitoring, complex manufacturing, or efficient logistics. At the same time, they are also a driver of technological and scientific innovation on many frontiers. Robots are used more and more to perform autonomous tasks with demanding precision constraints and in locations where humans cannot work. The most typical functions performed by robots in factories are tasks like handling, assembling, welding, surface coating, cutting, inspecting, and so on [5], [6].

One of the open research directions for multi-robot systems is represented by dynamic control of moving robots, for localization, mapping, exploration, and transportation tasks [7]. A team of robots can be used to carry loads from a point to another, or to manipulate the environment, which requires to keep into account decentralized asynchronous motion planning problems, such as on the fly collision avoidance, general motion coordination, formation generation and keeping, target search, or multi-robot docking [8].

Robotic agents can exploit an underyling communication infrastructure for the offload of time-critical, computationally exhaustive operations onto a distributed network [9]. Yet, for efficiency reasons, inter-node communications must be used sparingly and without a central control [10]. Bio-inspired approaches are also exploited in this context [11], [12] to develop cooperative behaviors among independent robots.

In this spirit, we claim that *Game Theory* [13] represents a good solution for a mathematical characterization of robotic agents in industrial environments, since it allows for the harmonization of multiple players with different and often contrasting objectives [14]. Thus, we study a multi-robot system in an industrial scenario through a game theoretic approach, which can provide further insight and suggest solution methods for different robot tasks [15].

The contribution of this paper is two-fold. First, we consider a static interaction between two robots with different objectives in a production line and we show how to trigger their coordination through the choice of proper Nash equilibria (NEs). Furthermore, we consider a Bayesian version of this scenario, to demonstrate how to include imperfections in the robot data acquisition and still retain a tractable game model.

The rest of this paper is organized as follows. In Section II we describe our model for the game-theoretic interaction, which leads to a formulation as a static game of complete information. In Section III we extend this to a Bayesian game, which is also discussed. Section IV concludes the paper.

II. Game Model

More and more frequently, large companies or factories adopt the use of robots that can automate part of the work so as to make it less burdensome for human personnel, faster and more accurate, minimizing errors as much as possible [5].

We consider the following model for an Industry 4.0 factory, divided into sectors [1]. First, we have a stage of material production, where, e.g., products are assembled [6]. This is followed by an automated quality control point managed by robots, and finally a packing and shipping department.

Notably, in the central section of quality control, which is the core of our analysis, we assume that two types of cooperating robots operate in pairs. We focus on such a pair, which includes (i) a robotic scanner (S) capable of detecting defects and imperfections in the objects produced, and (ii) another device, in the form of a robotic arm (A), able to grasp the objects [11] and move them to a location for their transport to the packaging and shipping department if declared as free of defects, or sending them back if they are flawed.

We assume that the scanner is designed to monitor different objects, from simple pieces with regular shape and smooth surface, up to complex items with multiple parts and irregular shapes. For the purpose of our game-theoretic analysis [15], we assume that S can choose between two operating modes, i.e., perform either a detailed scan mode (D) or a quick and less accurate scan (Q). The former action has a slightly higher cost c_D than the cost c_Q of a fast scan. S can still make errors in both cases, due to external and uncontrollable agents (for example: dirty scanning lenses). The second robot A, which moves the objects after the scan (either to the delivery or to return them back if flawed) is also assumed to have decisional ability: namely, A can choose the speed mode. For the sake of simplicity, we consider two modes of movement, i.e., a fast mode (F) and a slower cautious mode (C), with respective costs c_F and c_C, where $c_C > c_F$.

Mode F would be suitable, for example, if the item is once again a simple piece with regular shape, in which case it will be unlikely to fall. Conversely, a complex item, worth of a detailed scan, would also probably require a careful handling. Also, if the item is flawed, F is more appropriate than C, since it will save operating time. However, the advantage of increasing the delivery speed is nulled, and actually turns into a penalty, if a complex piece, theoretically free of defects, is unscrupulously sent to the delivery using mode F, since it increases the risk of damaging the item. The damage caused during the transport to the packaging department can be assumed to be worse than wasting time over a faulty piece, hence in this case C is preferred to F. At the same time, missing a defect is more serious than using more time for scanning a piece accurately; thus, if the piece is faulty, S should prefer to choose D over Q. Finally, we would like to achieve coordination among the robots, so we impose that it is better to choose consistent strategies, in which sense the strategy pairs (D,C) and (Q,F), considered to be *coherent*, should be incentivized [7].

We start with a scenario where the robots make their decision "simultaneously" for each object – in game theory jargon, this means that they choose their action unbeknownst to each other, which results in a *static game of complete information* [13], meaning that they choose either available action without preliminary coordination, but follow a rational principle of choosing what is best for their own and are aware of the aforementioned criteria, as well as their rationality.

This game can be formally described [15] as consisting of set of players {S, A} and their respective set of actions $\mathcal{S}_{\mathrm{S}}$ = {D, Q}, $\mathcal{S}_{\mathrm{A}}$ = {F, C}, and payoffs u_{S}, u_{A} that are described by this formula for both robots:

$$u_{\cdot} = P \cdot r - c_i + b_i\,,\ \text{for } i \in \{\text{D, Q, F, C}\} \qquad (1)$$

where c_i is the cost of the performed action, and b_i is an effectiveness increase/decrease assigned to action i as explained below, according to the values reported in Table I; r is a reward factor, whose value is $r_c = 1$ if the players choose a *coherent* pair of strategies, and $r_n = 0.5$ otherwise; and finally, P is just a normalization constant.

The effectiveness term b_i increases or decreases the payoff to represent an incentive for safer actions. For S, it is safer to play D because to misclassify an object is worse than wasting time over an accurate scan, so D $\succ$ Q. For A, the safe action is C because going slow is better than risking to damage a piece, so C $\succ$ F. These increases are also reported in Table I.

TABLE I
PAYOFF VALUES RELATED TO ACTIONS

Player	Action	Cost	Effectiveness
S	D (detailed scan)	$c_D = 2$	$b_D = 1$
	Q (quick scan)	$c_Q = 1$	$b_Q = -1$
A	F (fast mode)	$c_F = 1$	$b_F = -1$
	C (cautious mode)	$c_C = 2$	$b_C = 1$

We now analyze a first single round of the game, then we look for NEs in both pure and mixed strategies. The game is described in both normal and extensive forms. The normal form is reported in Table II, where Table III reports the numerical values of the parameters using $P = 10$ with costs and increases reported above in Table I. The extensive form is shown in Fig. 1.

In this single round game, there are two NEs in pure strategies: (D,C) and (Q,F). We can also look for NEs in mixed strategies, by applying the *Indifference Theorem* [13]. If we denote by β the probability of A playing F and with α the probability of S playing D, the following indifference relationships are found: $\beta = \frac{P+2}{2P}$, $\alpha = \frac{P-2}{2P}$. With the previous numerical choice of $P = 10$, we have $\beta = \frac{3}{5}$ and $\alpha = \frac{2}{5}$. The presence of multiple NEs implies that the system does not have a single operation point. While this thwarts the

TABLE II
STANDARD GAME NORMAL FORM

		Player A: F	Player A: C
Player S	D	$P\,r_n - c_D + b_D$ $P\,r_n - c_F + b_F$	$P\,r_c - c_D + b_D$ $P\,r_c - c_C + b_C$
	Q	$P\,r_c - c_Q + b_Q$ $P\,r_c - c_F + b_F$	$P\,r_n - c_Q + b_Q$ $P\,r_n - c_C + b_C$

TABLE III
STANDARD GAME NORMAL FORM WITH PAYOFF VALUES

		Player A: F	Player A: C
Player S	D	4, 3	9, 9
	Q	8, 8	3, 4

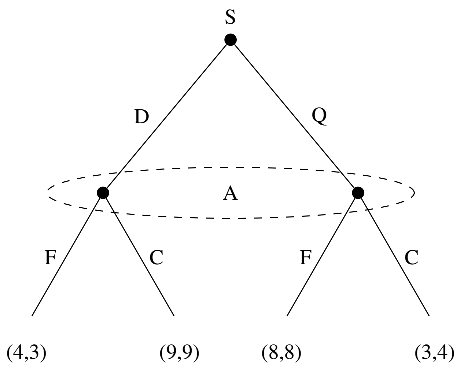

Fig. 1. Standard game extensive form

TABLE IV
NORMAL FORM FOR MM OR RR PLAYER TYPES

		Player A	
		F	C
Player S	D	$Pr_n - c_D + b_D = 4$ $Pr_n - c_F + b_F = 3$	$Pr_c - c_D + b_D = 9$ $Pr_c - c_C + b_C = 9$
	Q	$Pr_c - c_Q + b_Q = 8$ $Pr_c - c_F + b_F = 8$	$Pr_n - c_Q + b_Q = 3$ $Pr_n - c_C + b_C = 4$

option of making clear-cut predictions through game theory, it represents an opportunity for the development of engineering protocols to choose among the NEs [15].

III. BAYESIAN GAME

We also consider an incomplete information game, modeled as a Bayesian game [14]. In this scenario, according to the standard game theory formalization, an additional player is considered, called *Nature* [13], which in our case represents the possibility that our players may make mistakes. In our scenario, we assume that S commit scanning errors with probability p, while A with probability q. This means that if S makes mistakes it, recognizes the piece as irregular instead of classifying it as regular, so S wrongly chooses D instead of Q. In this case if A does not make mistakes, the cooperation will not be achieved because A identifies the right regular shape and plays F, leading to have (D,F), but we said cooperation is reached when robots play one of (D,C) or (Q,F) strategies.

The following four situations can happen, depending on the randomness of Nature's intervention: (i) MM: both S and A make a mistake; (ii) MR: S makes a mistake but A is right; (iii) RM: S is right and A is mistaken; (iv) RR: they are both right. So the game result changes based on these types, as the numerical values related to the utilities are the same for every action but the reward r is changed. Tables IV and V report the resulting normal forms based on the possible player types.

For the cases where both S and A are of the same types, the normal form of the game is reported in Table IV, while Table V shows the normal forms for different types (only either of the robots is in error).

TABLE V
NORMAL FORM FOR MR OR RM PLAYER TYPES

		Player A	
		F	C
Player S	D	$Pr_c - c_D + b_D = 9$ $Pr_c - c_F + b_F = 8$	$Pr_n - c_D + b_D = 4$ $Pr_n - c_C + b_C = 4$
	Q	$Pr_n - c_Q + b_Q = 3$ $Pr_n - c_F + b_F = 3$	$Pr_c - c_Q + b_Q = 8$ $Pr_c - c_C + b_C = 9$

The extensive form of the Bayesian game is shown in Fig. 2. For the sake of simplicity, we assume that both robots are equally likely to make mistakes with probability p. This leads to the normal form game reported in Table VI.

The Bayesian Nash Equilibria can be found from the following computation of the best responses (BR) [13]:

$$BR_S(\text{DD}) = \begin{cases} \text{FC} & \text{if } 0 \leq p \leq \frac{2}{5} \\ \text{CC} & \text{if } \frac{2}{5} \leq p \leq \frac{3}{5} \\ \text{CF} & \text{if } \frac{3}{5} \leq p \leq 1 \end{cases}$$

$$BR_S(\text{QQ}) = \begin{cases} \text{CF} & \text{if } 0 \leq p \leq \frac{2}{5} \\ \text{CC} & \text{if } \frac{2}{5} \leq p \leq \frac{3}{5} \\ \text{FC} & \text{if } \frac{3}{5} \leq p \leq 1 \end{cases}$$

$$BR_S(\text{DQ}) = \text{CF} \ \forall \ p \ , \ 0 \leq p \leq 1$$

$$BR_S(\text{QD}) = \text{FC} \ \forall \ p \ , \ 0 \leq p \leq 1$$

Table VII reports the resulting normal form of the game where the probability of making errors for S and for A is $p = q = 0.2$. We can observe that the BNE are indeed (DQ,CF) and (QD,FC). This implies that cooperation points, where both robots adopt a coherent strategy, are sought but only when the robots are of the same types. Failures in the system can steer the equilibrium away from using a coherent strategy. Thus, further research is needed to comprehend the Bayesian case with possible extensions related to the players revealing their type and also expanding the performance evaluation to the required cost for achieving coordination (possibly including an explicit communication among the robots) in this case [14].

TABLE VI
BAYESIAN NORMAL FORM WITH $p = q$

	FF	FC	CF	CC
DD	$-10p^2+10p+4$ $-10p^2+10p+3$	$9-5p$ $-6p+9$	$5p+4$ $6p+3$	$10p^2-10p+9$ $10p^2-10p+9$
DQ	$-4p+8$ $8-5p$	$p+3$ $4-p$	$p+8$ $p+8$	$6p+3$ $5p+4$
QD	$4q+4$ $5p+3$	$9-p$ $9-p$	$4-p$ $p+3$	$-6p+9$ $9-5p$
QQ	$10p^2-10p+8$ $10p^2-10p+8$	$5p+3$ $4p+4$	$8-5p$ $-4p+8$	$-10p^2+10p+3$ $-10p^2+10p+4$

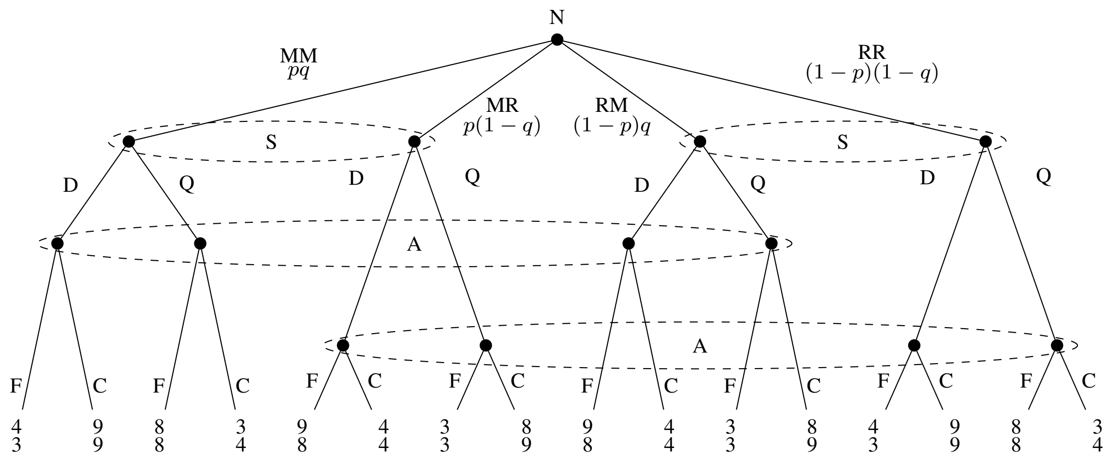

Fig. 2. Bayesian extensive form

TABLE VII
BAYESIAN NORMAL FORM WITH $p = q = 0.2$

	FF	FC	CF	CC
DD	5.6 4.6	8.0 7.8	5.0 4.2	7.4 7.4
DQ	7.2 7.0	3.2 3.8	8.2 8.2	4.2 5.0
QD	4.8 4.0	8.8 8.8	3.8 3.2	7.8 8.0
QQ	6.4 6.4	4.0 4.8	7.0 7.2	4.6 5.6

IV. Conclusions and Future Work

We contextualized an Industry 4.0 scenario of two interacting robots used for manufacturing processes [4], where cooperation among different agents can be established through the mathematical formalization of Game Theory [15]. We analyzed a static game of complete information, looking for NEs in such a setup. We also considered an extension of this setup to a Bayesian game, where system imperfections are kept into account such as misidentifications of the two robots happening with a certain probability. This leads to a Bayesian NE, which depends on the system parameters [13].

We posit that this kind of investigations can be expanded to many further scenarios. For example, one may include a Bayesian extension also to account for breakdowns of robots which become unusable, or the sporadic intervention of human operators that may counteract failures, but also they may decrease the speed of the system or making it overall worse in the long run. Future work may be devoted to explore these avenues that appear particularly promising.

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