A Trust-Based Team Formation Framework for Mobile Intelligence in Smart Factories

# A Trust-based Team Formation Framework for Mobile Intelligence in Smart Factories

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***Abstract*—In Smart Factories, Automated Guided Vehicles (AGVs) accomplish heterogeneous tasks as moving objects, restoring connectivity or performing different manufacturing activities into production-lines. These kinds of devices combine several capabilities, as artificial intelligence (visual and speech recognition, automatic fault detecting, pro-active behavior) and mobility, into the so-called "mobile intelligence". A typical scenario is represented by a workshop with a large number of mobile intelligent devices with associated agents, mutually interacting on their behalf. Here, to reach a given target by contemporary satisfying some basic requirements like effectiveness and efficiency, it is often necessary to organize ad-hoc teams of free-moving vehicles, sensors and smart devices. Therefore, a specific issue is the adequate representation of the reciprocal agent/device trustworthiness for advantaging such team formation processes within a smart factory environment. To this end, in this paper *(i)* we define a trust measure based on reliability and reputation of AGVs, which are computed based on the feedbacks released for the AGVs activities in the factory; *(ii)* we design a trust framework exploiting the defined measures to support the formation of virtual, temporary and trust-based teams of mobile intelligent devices; and *(iii)* we present a set of experimental results highlighting that the proposed trust framework can improve the workshop performance in terms of effectiveness and efficiency.**

***Index Terms*—Smart Factories, Mobile Intelligence, Team Formation, Multi-agent System, Trust**

## I. Introduction

The fourth industrial revolution has led to the development of smart factories [1] whose production adaptability is enabled by the presence of self-organizing production-lines. At the same time, self-organization implies that tasks are distributed across more processing units. In particular, all the activities occurring within such distributed, fine-grained and possibly movable processing units, as information exchange, raw materials delivery and work-in-progress, lead to the adoption of wireless communication systems and of free-moving vehicles.

Guided vehicles like laser guided vehicles, rail guided vehicles, mobile robots, unmanned vehicles, are capable of performing pre-defined tasks such as moving objects for short destinations, repeatedly welding, or other tasks on the production-lines. Enabled by the technological advancements, these devices combine computational, communication and mobility capabilities, providing the so-called "*mobile intelligence*". Such flexible exploitation of the mobile intelligence along with the tight integration of wired and wireless communications, as wired/wireless fieldbus networks and wireless sensor networks [2], pave the way towards an effectiveness and efficiency (*E&E*) improvement.

To accomplish this goal, free-moving vehicles, sensors and smart devices can be organized in ad-hoc teams with a suitable composition for a given target. This solution is quite common if each workshop area of a Smart Factory demands flexibility, adaptivity, and the involvement of different materials, assembling tasks and devices (e.g., a workshop area dedicated to the assembly on-demand different models of vehicles with a high level of customization, like top-cars).

To deal with the scenario described above, a number of Internet of Things (IoT) architectures and standards have been developed based on communication, sensory, information and networking technologies [3]. However, none of the past proposals, to the best of our knowledge, has been tailored to appositely support the formation of teams among mobile intelligent devices within a workshop area of a Smart Factory.

If mobility and social interactions are key to enable the teams formation within the Smart Factory context, conversely, dynamically determining the most suitable team members to accomplish a given target is notably challenging, due to the mobile nature and the heterogeneous features (skills, autonomy, etc.) of the devices. A first approach present in literature proposes the teams formation on the basis of both structural and semantic similarities existing among "partners" [5]. However, these properties could not be adequate in a Smart Factory for a twofold reason: the potential high variability in the task-specific devices' performance, and the absence of historical data or central, shared repository. Alternatively, to provide devices with a reasonably high probability to have positive interactions, ad-hoc, temporary teams can be formed on the basis of some social properties existing among the team structure members. In such direction, a promising criterion consists in forming teams on the basis of the members' trustworthiness levels [6]. In this case, to dynamically compute the trustworthiness of a large number intelligent devices (and associated agents) and form teams, a solution is selecting members on the basis of both the *reliability* shown in performing their own tasks and the *reputation* gained within the workshop area (i.e., agent community) [7]. Such two information, respectively expressed in terms of efficiency and effectiveness, are usually embedded in a single measure named *trust* and can be shared within the workshop area (thus obviating the need of a centralized repository and also providing a higher fault tolerance, concurrency, etc.). To this end, a suitable solution is associating a device with one or more software agents, leveraging on the well-known social attitude, smartness and coordination capabilities of Multi-Agent Systems (MAS) [4].

### A. Our contribution

Aiming to form effective and efficient AGV teams in the mobile and collaborative Smart Factory context previously described, in this paper we provide the following three contributions:

First, we present a new model that defines the devices' reliability, reputation and trust measures, i.e., the efficiency, effectiveness and trustworthiness of the agents with respect to the activities they perform on the production-line. Therefore, in our model we consider:

- the effectiveness of an AGV, measuring its level of appreciation received for its contributions from the items customers;
- the efficiency of an AGV, measuring its capability to correctly perform one or more specific tasks on the production-line;
- the trustworthiness of an AGV, combining its efficiency and effectiveness (purposely weighted based on the factory policies) to obtain a single, characterizing, synthetic measure.

As second contribution, we design a strategy to form AGV teams by leveraging the measure of trustworthiness defined above. In particular, AGVs are classified based on their time availability (i.e., the time they need to accept a new task) suitably weighted by the trustworthiness value which, in its turn, embeds efficiency and effectiveness information combined accordingly to the factory policies. AGV teams are hence formed by choosing the top classified in this ranking.

Thirdly, for exploiting the aforementioned benefits featuring the agent-based computing paradigm, we introduce a MAS on the workshop areas to support the formation of virtual, temporary teams of mobile intelligent devices. In particular, by associating each AGV with a software agent that automatically updates its trust information, the MAS will allow the automatic implementation of the team formation strategy mentioned above.

We tested our framework and a team formation strategy on a simulated agent-based scenario, showing that combining mobile intelligence, team formation, reliability, reputation and trust information leads to a measurable improvement of the simulated workshop area in terms of *E&E*.

### B. Advantages and limitations of our approach

An important advantage introduced by our approach with respect to the state-of-the-art is represented by the capability of our trust framework to form efficient and effective AGV teams, also in presence of highly dynamic and non homogeneous environments. As matter of fact, even in the most critical scenario of the simulation set (which is given by a combination of maximum loss of *E&E*), our team formation strategy based on our trust model leads to a significant improvement of both *E&E* of the production-line. We highlight that our approach is the first attempt, at the best of our knowledge, to obtain such an improvement using a distributed MAS without the need of a central management system (which, instead, very likely would introduce an unacceptable overhead).

However, we have to also highlight that our approach introduces a cost in terms of average "loss" time (in seconds) for single AGV and working day. In other words, the strategy adopted to form AGVs team is not optimized with respect to the AGV' time availability because it is suitably weighted by the AGV's trust score. To evaluate this "loss" of time, we have performed apposite simulations, presented in Section VI, showing that this limitation is negligible with respect to the obtained improvement in terms of *E&E*. Finally, although we have used realistic simulation parameters for modelling the workshop areas, real situations contemplate random events whose influence on our model performances has still to be accurately determined.

### C. Structure of the paper

The remaining of the paper is structured as follows. Section II provides an overview on the related literature. Section III describes the proposed framework scenario while Section IV deals with the trust model. Section V makes a connection between the contributions of these two Sections (i.e., the main architecture presented in Section III and the trust model of Section IV), showing how the trust model can be exploited to perform a team formation activity on the AGVs of the smart factory in a distributed way. The results of our experiments are discussed in Section VI. Finally, in Section VII conclusions are drawn.

## II. Related work

Nowadays, the IoT represents an enabling technological paradigm for the Industry 4.0, Smart Factory and supply chain management [8]. Indeed, the IoT revolutionized the information exchange and codification processes [9], disclosing the benefits of a flexible and smart industry where devices are capable of exchanging real time information. This enables a high production flexibility by means of real time parameter optimization and customization as well as an extensive integration among customers, companies, and suppliers [10].

AGV are widely adopted in smart cyber-physical manufacturing contexts to perform novel, fundamental activities like real-time monitoring, connectivity restore and collaborative control [11]. For instance, Theunissen et al. [12] illustrate a real case study about smart manufacturing shopfloors where a smart AGV eases the collaborations between typical workers and robots. The proposed smart AGV system uses radio frequency identification (RFID) and wireless communication standards for interactions. The authors demonstrate the contribution given by the adoption of the AGV by illustrating a few results and observation obtained from the real case study. In [13], AGVs are used in a hybrid (fixed and mobile) industrial wireless sensor networks featured with a task-oriented model. The authors design a heuristic modeling method to assign tasks to a controller as well as a collaborative routing algorithm used for the AGVs mobility. The experiments have shown that the mobility features of the AGVs support promptly network repair in case a link fails or the detected quality is low, thus improving the reliability of the industrial IoT system. Authors of [14] address the problem of AGV planning in a workshop through a co-evolutionary framework which supports the whole production process. The twofold goal is the reduction of the material transporting costs in the manufacturing process and the introduction of flexibility as well as reconfiguration capabilities. Moreover, recent advances of low-latency communication technologies as 5G allowed AGVs to form groups of coworkers which are able to communicate very efficient way, as described in [15].

All these works [12], [13], [14] demonstrate the advantages coming from the adoption of AGV in smart manufacturing scenarios. Our proposal relies on this research step, with the AGVs which are enhanced through the multi-agent technology and fully integrated with the trust system.

In this direction, an interesting study about group formation for smart cooperating devices in a smart factory can be found in [16], where the specific requirements of Cyber Physical Logistics Systems are illustrated together with a real-world scenario comprising both autonomously and cooperatively agent-based devices. Similarly, in [17] software agents are employed to accomplish tasks like controlling the materials handling and factory scheduling to automate the factory environment and its activities. Then, in [18] an agent-based controller is deputed to find the optimal, collision- and deadlock-free motion planning of its associated AGV. In the context of the Supply Chain Management, the authors [19] present and discuss a real case study to illustrate the applications and advantages of an Industrial IoT (IIoT) and design a framework which integrates neutrosophic Decision Making Trial and Evaluation Laboratory technique with an analytic hierarchy process. The combination of the two techniques allows the operators to deal effectively with uncertain and incomplete information, in order to overcome the challenges of traditional Supply Chain Management. A recent work of Wan et Al. [20], instead, illustrates a combined solution for the IIoT: an OLE (Object Linking and Embedding) for process control technology; a software defined industrial network, and; a device-to-device communication technology to achieve efficient dynamic resource interaction and management (to this end, an ontology modeling with multi-agent technology is used). With respect to these contributions, in our proposal the effective team formation is performed by means of a trustworthiness measure whose implementation (and the preliminary information exchange it requires) is enabled by the exploitation of the multi-agent technology in the entire framework.

### A. Trust-based collaborative approaches in IoT contexts

Trust and reputations systems, as well as group formation, can play a crucial role in IoT contexts: while cryptographic techniques are designed to safeguard privacy and authentication [21], trust and reputation systems allow providing an effective support to estimate the trustworthiness of potential partners. One of the basic building block of trust measures, as we discuss later in this work, is the reliability measure obtained from direct experiences. In addition, any potential partner or service customer might wonder how much the community (or a subset of it) trusts a certain peer [22]. As a consequence, trust is often estimated by evaluating direct agents experiences (reliability) and/or opinions of others (reputation). Finally, reliability and reputation are usually arranged in a single synthetic measure as, for instance, in [23]. To this regards we report, in the following paragraphs, a few relevant efforts to integrate trust and reputation models in IoT contexts.

The model proposed in [24] provides a dynamic trust management protocol which exploits the "social nature" of relationships among IoT devices to perform a trust-based service composition. Authors of [25] describe a trust system which is able to follow the evolution of social relationships over time; it has the capability to adapt itself to the possible trust fluctuations.

In [26], authors emphasize that IoT devices hold heterogeneous skills which are enabling for composite and complex tasks execution: therefore, IoT devices can exploit direct experiences and available recommendations (i.e., first and second-hand information/observations) to assess the trustworthiness of their peers and accordingly to match services' demand and offer.

BETaaS [27] is an approach for Machine-to-Machine applications that integrates a trust model (encompassing different aspects as security, QoS, scalability, availability and gateways reputation) to evaluate smart devices reliability by monitoring them and their behaviors.

Smart devices can form groups of like-minded peers by means of their social interactions and mutual trust evaluation [28]. Nevertheless, a few, very important aspects, such as scalability (e.g. billions of devices) and countermeasures against bad-mouthing attacks, have to be considered when forming trust-based groups in IoT environments. To this regards, in [29] it is proposed an approach for scalable trust-based IoT clustering joined with an intelligent method for countering bad-mouthing attacks on trust systems. Also in this work the authors take into account trust computation and trust-based migration of IoT nodes from one cluster to another. The convergence among IoT, software agents and cloud computing [30] to form groups of agents (each one associated with an IoT device and living on the cloud) has been recently studied in [6], where an algorithm to form agent groups on the basis of information about reliability and reputation collected by the agents is presented. The experimental results prove that the proposed approach leads to form groups with high values of mutual trust.

The researches discussed above prove how trust and reputation systems can give a contribution to the organization and collaboration of "social" IoT devices. In addition, in our proposal, the trust system is supported by the adoption of the multi-agent technology, as detailed in the next Section III.

## III. The Application Scenario

In the next future, cooperative assembly methodologies will lead the manufacturing activities of most of companies. Performance of the assembly methodologies strongly depends on the capability of each actor to cooperate in a highly coordinated way with its humans or robotic coworkers. Let consider a production-line requiring the cooperation of heterogeneous smart AGVs and human workers to reach a specific goal: for example, as depicted in Figure 1, a smart factory and its working areas (dashed line rectangles) where cars are assembled. The movements of cars, AGVs teams and humans through the working areas (represented by dashed-dotted lines) gives the idea of that swarm intelligence to be implemented in the production-line and enabling the cooperation of multiple intelligent actors (humans and AGVs) for assembling products

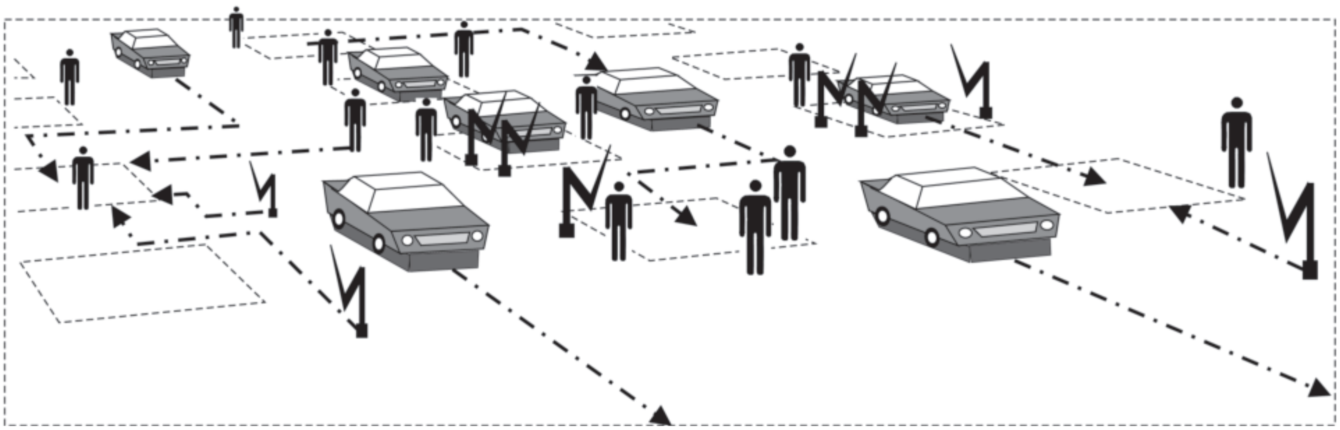

Fig. 1. An example of smart factory adopting a swarm intelligence approach to assembly cars

(the cars). In this Section we present such a kind of scenario, relying on the trust framework we later describe.

More in detail, in the proposed scenario, we assume the presence of a variable number of smart AGVs, as it depends on the adopted processing technique. AGVs, in their turn, have different typologies (according to their tasks, like transportation, welding, etc.) as well as efficiency (depending on their model, age, sensing capabilities, usury, etc.) and effectiveness (e.g., skills and so on) values. Production-lines adopting a swarm assembly approach have to face such heterogeneity to form suitably sets of coworkers (human and AGVs) for reaching the desired production goals in the required time.

Enabled by the well-known social, smart and cooperative attitudes of software agents [4], we also assume that each AGV is assisted by a software agent that, on its behalf, will support its working activity within the team of coworkers (see Figure 2).

At the same way, production-lines are organized by a software agent named *Manufacturing-Manager* (MM), that executes the tasks to produce the items by forming the "best" team/teams of AGV coworkers. In particular, the MM selects the AGV members by choosing the best available smart AGVs (in terms of *E&E*) on the basis of their trust measures (see Section IV), built over time on the basis of their past activities in the workshop area. More formally, let W be the workshop area of our smart factory and let SC be the daily set of customers requiring to the smart factory the assembly of a customized item. Each customer $c \in SC$ has a reference to a software agent called Manufacturing Manager MM. The goal of a MM is building for each item the best team/teams of AGVs capable of optimizing the production process in terms of *E&E*. We have introduced a MAS in our framework aiming to distribute the information load over the entire set of AGVs, avoiding to centralize it into a unique repository. This way, in order to reach its goal, MM periodically updates the measures of efficiency and effectiveness of the workshop agents, and consequently computes and updates the trustworthiness measure, combining efficiency and effectiveness as described in the next Section. The MM saves a copy of these values in its internal memory, while each agent that has interacted with the MM saves a local copy of its measures. Therefore, when the agent will interact in the future with a novel MM, it will transmit the information about its efficiency, effectiveness and trustworthiness, as a sort of references. In the next Section, we will describe the trust model we have adopted to represent the measures of efficiency and effectiveness, and how we have integrated them into a unique measure of trustworthiness. Then, in Section V we will show how this model can be used in our framework to perform the team formation activity in a distributed way.

## IV. The Trust Model

In this section we present the trust model specifically designed to take into account the *E&E* of AGVs within a smart factory.

In particular, in the following we define:

- the AGV *effectiveness* as the the customer satisfaction with respect to the job performed by the AGV; namely, the effectiveness represents the reputation that an AGV has in the customer community;
- the AGV *efficiency* as the capability of complying with the assembly constraints (e.g., time) during the product assembly process; namely, the efficiency represents a sort of reliability with respect to the production-line operation;
- the AGV *trustworthiness* as a single trust measure taking into account both *E&E* to suitably drive the AGV team formation processes.

We assumed that, in a controlled environment such as a smart factory, there are no malicious agents so that specific countermeasures against unsuitable behaviors (e.g., collusive, complainer, alternate, whitewashing and so on) aimed to gain undue advantages are not necessary to be implemented.

### A. Definition of Effectiveness, Efficiency and Trustworthiness

The AGV *Effectiveness* ($\rho$) refers to the level of appreciation that the AGV receives for its contributions from the items customers. The value of $\rho$, with $\rho \in [0,1] \subset \mathtt{R}$, is computed on the basis of the feedback $\psi$, with $\psi \in [0,1] \subset \mathtt{R}$, provided by the customers to the agent (i.e., the AGV). More formally, $\rho$ is computed as:

$$\rho^{new} = \beta \cdot \rho^{old} + (1 - \beta) \cdot \psi \tag{1}$$

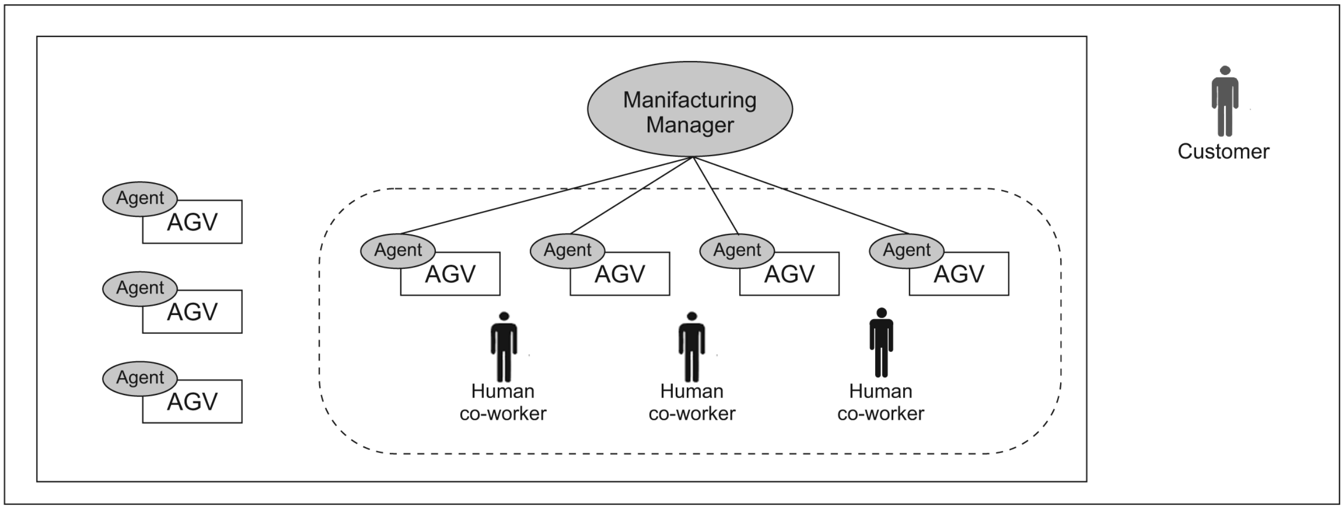


Fig. 2. Agent-based architecture

where $\beta \in [0,1] \subset \mathtt{R}$ is a parameter to assign a certain relevance to $\psi$ (which is referred to its latest task) in updating $\rho$ with respect to its current value, i.e. the feedback it received in the past.

The AGV *Efficiency* ($\sigma$) is the capability of the smart AGV to correctly perform one or more specific tasks on the production-line. This capability is measured by $\sigma$, with $\sigma \in [0,1] \subset \mathtt{R}$, on the basis of objective measures ($m$) (e.g., the time required to complete a task) that can be suitably combined in a single measure $\phi \in [0,1] \subset \mathtt{R}$, with $\phi = f(m_1, \cdots, m_n)$. More formally, $\sigma$ is computed as:

$$\sigma^{new} = \alpha \cdot \sigma^{old} + (1 - \alpha) \cdot \phi \tag{2}$$

where $\alpha \in [0,1] \subset \mathtt{R}$ is a parameter giving more or less relevance to $\phi$ in updating $\sigma$ with respect to its current value (i.e., the past tasks of the AGV can be considered more or less relevant with respect its latest one).

The *Trustworthiness* ($\tau$) combines *Efficiency* and *Effectiveness* (i.e., reliability and reputation) to obtain a single synthetic measure characterizing a specific agent (i.e., AGV). The model of trust we propose in this paper is the well-known linear combination of reliability measures already used with substantial results in our previous works (e.g [6], [23]) but contextualized in other multi-agent domains. This proposal seems adequate given the reasonable supposition that, if a given increment of efficiency $\Delta\sigma$ (resp. effectiveness $\Delta\rho$) generates a given increment of trustworthiness $\Delta\tau$, then the percentage ratio $\frac{\Delta\tau}{\Delta\sigma}$ (resp. $\frac{\Delta\tau}{\Delta\rho}$) should be the same for any increment of $\Delta\sigma$) (resp. $\Delta\rho$). Obviously, other proposals are possible, supposing that in some particular contexts the establishment of mathematical relationships between effectiveness (resp. efficiency) and trustworthiness might not be linear. The experiments we describe in Section VI show that the linear model very well reproduces the considered simulated scenario. Future experiments on real scenarios could disclose the necessity of different mathematical models for best approximating other measured results. More formally, $\tau$ is computed as:

$$\tau = \gamma \cdot \sigma + (1 - \gamma) \cdot \rho \tag{3}$$

where $\gamma \in [0,1] \subset \mathtt{R}$ is a parameter giving more or less relevance to $\sigma$ with respect to $\rho$; $\gamma$ is to be suitably set according to the factory policies in terms of *E&E*.

As detailed in Section VI, in our experiments we have used a value $\gamma = 0.4$ for giving more importance to the effectiveness with respect to the efficiency (generally, producing a good item which satisfies the customer has priority over chasing extreme assembly rates), but without exceeding (we have limited such difference of importance to 10%). But the setting of $\tau$ is arbitrary, and we plan for the future to make a sensitivity analysis of the model performances with respect to this parameter.

## V. Team Formation

In this section, we argument how the architecture described in Section III and the trust model introduced in Section IV can be usefully combined to form AGVs teams within the smart factory.

First of all, we recall that our framework associates a software agent to each AGV, thus enabling the update, storage and share of its effectiveness, efficiency and trust information over the entire workshop/MAS through the MM agent. Just the exploitation of the agent-based computing paradigm represents an important advantage of our framework, avoiding the necessity of central factory management server and its consequent drawbacks (bottleneck effect, single point failure, communication overhead, etc.).

Furthermore, we remark that the introduced trust model allows the team formation activity by taking into account both present and past AVG results, in terms of *E&E*. In order to exploit such a possibility, based on the measure $\tau$ above defined we here present the strategy described below to form AGV teams. Each MM agent classifies AGVs on the basis of their time availability $TA$ (i.e., the time the AVGs need to accept a new task) suitably weighted on the trustworthiness $\tau$ value which, in its turn, embeds *E&E* information combined accordingly to the factory policies. AGV teams are hence formed by each MM by choosing the top classified in this

ranking.
More formally, a distributed algorithm is executed by the set $A = \{a_0, a_1, .., a_n\}$ comprising all the $n$ AGV agents and the MM agent, where $a_0$ is the MM agent and $a_i$ is the i-th AGV agent. The algorithm is composed of five tasks, namely the *formation assignment* task, the *request* task, the *response* task, the *selection* task, and the *team formation* task. While the formation assignment, request, selection and team formation tasks involves by the MM agent $a_0$, the response task is executed by each agent $a_i$, $i = 1, .., n$. In detail, the five tasks operate as follows:

1) **formation assignment task:** the MM agent $a_0$ receives by its administrator (usually, a human manager or a workflow process) the assignment of forming a team. To this end, the MM agent $a_0$ yield as inputs for the task:
   - the number $k$ of agents required for the team formation;
   - the maximum allowed waiting time $st$ before starting the team formation;
   - the minimum trustworthiness value $mt$ required to an AVG for joining the team.
2) **request task:** the MM agent $a_0$ sends an information request to each agent $a_i$, $i = 1, .., n$, for obtaining its time availability $TA_i$, representing the time that $a_i$ needs to accept the task, and its trustworthiness $\tau_i$.
3) **response task:** following a request information from the MM agent $a_0$, an agent $a_i$ has to compute the required values before providing a reply:
   - its time availability $TA_i$, based on the other tasks in which it is already involved;
   - the trustworthiness $\tau_i$ by combining the measures of efficiency $\sigma$ and effectiveness $\rho$ as described in Section IV.

   Note that each agent $a_i$ continuously updates these two measures according to both the time consumed for completing the various tasks in which it has been involved and the feedbacks received by the customers. After these operation, both $TA_i$ and $\tau_i$ are sent to the MM agent $a_0$ (note that the value of $\tau_i$ that is sent to MM agent $a_0$ is computed with respect to the last update of $\sigma_i$ and $\rho_i$).
4) **selection task:** the MM agent $a_0$ continuously monitors the list $R$ containing all the responses received by the AGV agents, containing the pairs $(\sigma_i, \rho_i)$; for each $i = 1, .., n$, the MM agent $a_0$ computes the following score:

$$R_i = TA_i \cdot \tau_i \tag{4}$$

   Therefore, the MM agent $a_0$ deletes from the list all those agents $a_i$ whose $TA_i > st$ or $\tau_i < mt$, since their associated AGVs are not suitable to contribute to the team formation. Moreover, the MM agent $a_0$ maintains the list $R$ ordered by a decreasing value of the score $R_i$.
5) **team formation task:** when the time $st$ is reached, the MM agent $a_0$ examines the list $R$ and provides a response to its administrator, that will contain:
   - the list of the first $k$ agents of $R$, if the cardinality of the list $R$ is greater than or equal to $k$.
   - a notification that the team formation process has failed, otherwise.

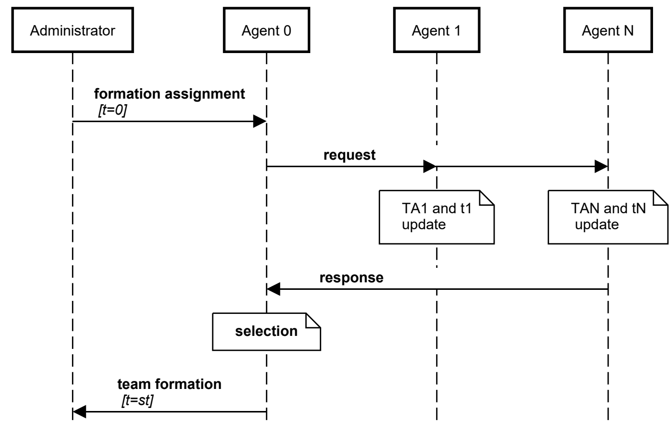


Fig. 3. Team formation algorithm: in bold the tasks executed by Administrator, Manufacturing Manager $a_0$ and other agents $a_i$.

A sequence diagram representing the distributed team formation algorithm is reported in Fig. 3.

Note that all the tasks described above are independently performed by the agents of the set $A$, avoiding the manufacturing manager the need of maintaining a central repository of the trustworthiness information regarding the AGVs. In that case, the central repository management would imply a continuous updating of the AGV information with a consequent overhead for the internal communication network, obviously resulting in a loss of efficiency. Note also that other and more sophisticated strategies could be adopted: however, inspecting these alternative strategies is beyond our primary aim, which instead consists in verifying that trustworthiness information about smart AGVs can be profitably exploited also in the production-line of an smart factory scenario.

## VI. Experiments

In order to test and validate the proposed framework, we simulated a smart factory scenario in which both the production-line and swarm assembly organization are assisted by a MAS. We simulated a number of working days, where in each day a random number of customers' orders must be satisfied. The assembly of each item needs four highly customized and serial manufacturing processes. In turn, each manufacturing process is carried out by three mobile smart AGVs without the participation of humans as coworkers or supervisors.

Furthermore, we assumed that *(i)* AGVs have heterogeneous performance in terms *E&E*, and *(ii)* the item manufacturing process is denoted by a high customization level. The above assumptions imply that *(i)* a different amount of time is required to each AGV for completing its task (performance and customization), and *(ii)* a different appreciation (i.e., the feedback $\psi$) is given by the customer who required its assembly.

As introduced in Section III, to form the best AGV team for a specific manufacturing task, a MM agent is associated with a production line and it supports the assembly of each item ordered by a customer $c \in CS$. The MM interacts with the software agents associated with the AGVs to form, at a given time, the best possible team by optimizing the members selection with respect to the availability trustworthiness of the AGVs.

For each AGV, after each manufacturing task, reliability ($\sigma$), reputation ($\rho$) and trust ($\tau$) are updated.

### A. Experimental settings

The smart factory has been simulated by considering a single swarm assembly production-line with the following parameters (also reported in VI-B):

- $60$ working days, each one formed by $8$ working hours;
- $150$ customers' orders per day;
- $1$ production-line consisting of $25$ assembly slots, where an item changes its slot after each manufacturing task;
- $4$ serial customized manufacturing tasks for each item;
- $400$ AGVs (i.e., $100$ for each of the $4$ required item manufacturing task) are active on the production-line.

The parameters introduced above play an important role in driving the production- line operation and the AGVs behaviors: therefore, after an apposite inquire, we retrieved and set the parameters with those common values actually adopted in some European factories assembling cars.

After some preliminary tests, the trust framework was set as follows:

- the values of $\sigma$ and $\rho$ have been both initially set to $1.0$, adopting the strategy of giving maximum reliability in absence of information and then varying this reliability over the time, based on the experience;
- the value of $\tau$ has been initially set to $1.0$;
- the parameters $\alpha$ and $\beta$, respectively used to update $\sigma$ and $\rho$, have been set both to $0.95$, aiming to consider a sufficiently little variation of both *E&E* with the new feedbacks obtained over the time;
- the parameter $\gamma$, used to update the $\tau$ has been set to $0.4$, following the considerations explained in Section IV.

### B. Results

We simulated different scenarios where each AGV's *E&E* values vary in different ranges, and within them in a uniform manner. For the AGV efficiency, we assumed that the loss of efficiency varied up to a maximum of the $1$, $2$, $3$, $4$ and $5\%$. Similarly, for the AGV effectiveness we assumed that the loss of effectiveness varied up to a maximum of the $5$, $10$, $15$, $20$ and $25\%$.

Figures 4 and 5 show the results related to the accuracy of $\sigma$ and $\rho$ to represent such behaviors for some AGVs. These experiments highlighted that the two measures reflect a realistic situation in which the system properly reacts to an increasing loss of *E&E*. We only observed a very negligible loss of sensitivity for $\sigma$ when the AGV performances are very high. For example the curve labelled $1\%$ of Figure 4 is partially overlapped with the curve in the same plot labelled $2\%$.

The second set of experiments focuses on the parameter $\tau$, considering it as an indicator of the performance of whole the production-line with respect to specific policies (represented by the parameter $\gamma$, see Section IV). Figure 6 reports the results for $\gamma = 0.4$: we observe that the computed values of $\tau$ reflect the behaviors of the AGV in terms of *E&E*. Figure 7 reports the trend of the Trustworthiness for three AGVs which represent respectively the best, the median and the worst in terms efficiency/effectiveness (i.e., the best: $1\%/5\%$, the middle: $3\%/15\%$, and the worst: $5\%/25\%$). We observe that Figures 4,5 and 7 contain some slight peaks and valleys. The presence of such shapes is a consequence of simulating a variability in the *E&E* loss: such choice has been made in order

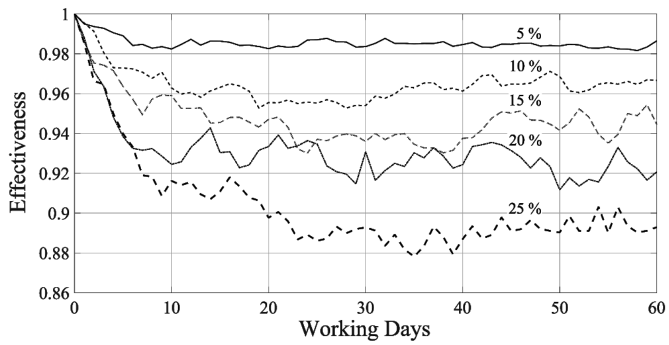


Fig. 5. Effectiveness reputation ($\rho$) for different losses of effectiveness varying from $-5\%$ to $-25\%$ with step $-5$.

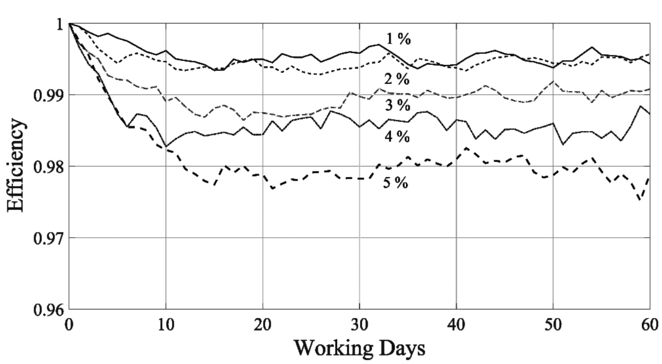


Fig. 4. Efficiency reputation ($\sigma$) for different losses of efficiency varying from $-1\%$ to $-5\%$ with step $-1$.

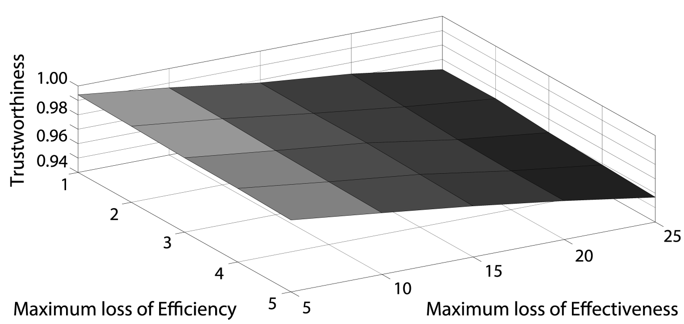


Fig. 6. Average Trustworthiness for different values of *E&E* loss respectively varying from $-1\%$ to $-5\%$ with step $-1$ and from $-5\%$ to $-25\%$ with step $-5$.

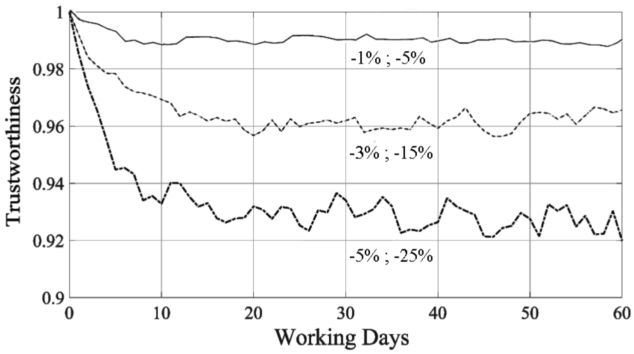


Fig. 7. Trustworthiness for working days for the scenarios (-1%; -5%), (-3%; -15%) and (-5%; -25%) in terms of efficiency and effectiveness loss, respectively.

to represent a real word scenario, as detailed in the beginning of this section. In other words, such behavior is compliant with both the simulated parameters and the behavior expected in a real word scenario.

Finally, the last set of experiments we present focuses on the capability of our trust framework to form efficient and effective AGV teams. To this aim, we considered the most critical scenario of our simulations set, which is given by a combination of maximum *E&E* loss of the $5\%$ and $25\%$, respectively. The results of these experiments are shown in Figures 8 and 9.

In particular, Figure 8 represents the overall advantages, in terms of $\sigma$, $\rho$ and $\tau$, obtained by considering all the 60 simulated working days. The advantage in terms of $\sigma$ has been calculated by adding the differences between the efficiency value of the AGVs chosen by means of the strategy proposed in Section IV to form an AGV team for a manufacturing task and that of the AGVs that would be chosen only considering temporal availability. Same with the effectiveness and the trustworthiness measures. This experiment proofs that our trust framework allows improving both *E&E* of the production-line. However, all this has a cost, in terms of average daily "loss" of time (in seconds) for AGV, as reported in Figure 9. In other words, the strategy adopted to form AGVs team is not optimized with respect to the AGVs' time availability because it is suitably weighted on the AGV's trust score (i.e., also its *E&E* is taken into account in the AGV selection process). Therefore, the chosen AGV might not have the best time availability but the best ranking in terms of weighted time availability (see Section IV). To evaluate this "loss" of time, more simulations have been carried out, also for periods up to 365 working days, obtaining values that are always around one minute, in average with respect to all the AGV set. This average loss of time, strictly related to the available hardware over which the team formation algorithm runs, could be considered acceptable in the light of the improvement obtained in terms of *E&E*.

## VII. Conclusions

Forming AGVs teams in a mobile and distributed environment as smart factories might lead devices to interact with interlocutors whose effectiveness and efficiency (*E&E*), with respect to their specific skills, are not the best possible in the workshop area. In this paper, we argued that a possible way to form a team is selecting its members on the basis of their reliability and reputation. Therefore, we introduced the definition of device's reliability, reputation and trust with respect to its associated agent's effectiveness, efficiency and trustworthiness, and then we presented a novel trust-based framework to support the formation of virtual, temporary teams of mobile intelligent devices in the workshop area. The simulation we have performed on an industrial scenario modelled in compliance with realistic settings (aiming to consider our approach as suitable for real industrial applications) highlighted that combining reliability, reputation and trust information leads to a measurable improvement in terms of *E&E* of the workshop area. Moreover, we have observed that also the computed values of trustworthiness reproduce the *E&E* of the AGVs. These simulation results, obviously, need to be confirmed to further experiments on real environments. Indeed, some random, unpredictable events due, for instance, to the generation of faults, can affect the framework performances. We plan to address this aspect in our ongoing research.

As future work, we will assess the suitability of the framework for the context of Industrial Cloud, aiming to implement a collaborative production process among multiple smart factories and related asset. We finally observe that Group Role Assignment (GRA) and the E-CARGO (Environments - Classes, Agents, Roles, Groups, and Objects) model are declared as a good way to support team formation [31], [32], [33], [34], therefore it is valuable to investigate the team formation with GRA and E-CARGO.

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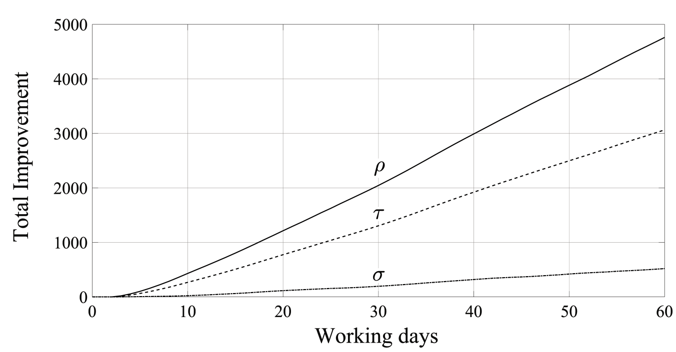


Fig. 8. Advantage given by the trust framework in terms of $\sigma$, $\rho$ and $\tau$.

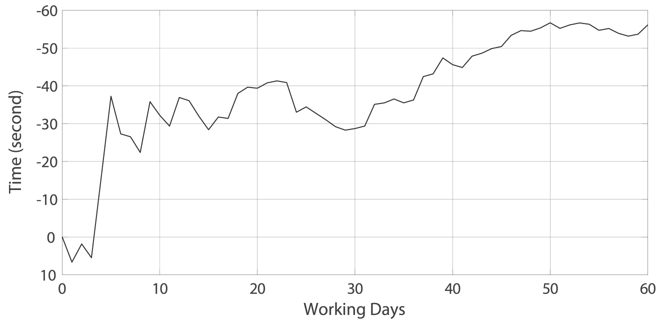


Fig. 9. Average time "loss" for AGV.

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