Multi-Agent Task Allocation to Minimize Costs of Energy Consumption in the Presence of a Price-Based Demand Response Program

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***Abstract*—As a result of Demand Response (DR) programs implementation in the industrial sector, varying electricity prices based on Time-of-Use (ToU) rates are becoming more common, replacing traditional flate-rates per unit of energy consumption. On the other hand, increased automation of industrial facilities is gaining interest due to their reliability, flexibility, and robustness. However, it is necessary to determine a suitable task schedule in order to ensure their cost-efficiency and maximize profits. In this study, a Market-Based approach is considered to solve the Multi-Agent Task Allocation (MATA) problem for a group of homogeneous agents and tasks. While most previous studies model the problem considering flate-rates for electricity consumption, the main contribution of this study is accounting for the implementation of a DR program with varying ToU rates. The effects of optimizing the task allocation process on the costs incurred are investigated and compared to the effects of random assignment. Four different case studies are analyzed considering different-sized maps and number of tasks. The results show the computational efficiency of the proposed algorithm and its ability to massively decrease the electrical charging costs.**

***Index Terms*—Market-Based Approach, Price-Based Demand Response, Task Allocation, Time-of-Use, Optimization.**

I. Introduction

A. Background and Motivation

Increased interconnection of cyber-phsical systems is accelerating automation of the industrial sector as part of the fourth industrial revolution (I4.0). A key element therein is the Internet of Energy (IoE), emerging through incorporation of advanced metering and communication in Smart Grids (SG) infrastructure, with an emphasis on the demand-side such as Smart Homes (SH), Smart Buildings (SB), and Smart Factories (SF). In the IoE paradigm automation of all or most required operational actions is necessary, with higher-level intervention reserved to emergeny situations or system planning. [1]

For industrial applications, researchers are continuously proposing new methods for better coordination of several autonomous systems working together to carry out certain predetermined tasks [2]. Such systems are refered to as Multi-Agent Systems (MAS), and their power lies in the cooperation capabilities that could lead to more efficient and feasible process handling as opposed to relying on a single agent to carry out the process from start to finish. Recent technological advancements in the field of autonomous and intelligent systems are opening several research fronts in which developed methods and algorithms could be extended to a wide spectrum of multi-disciplinary applications, from search and rescue missions [3], to automated industrial facilities [4] and coordinated management of Electric Vehicle (EV) fleets [5].

The initial costs of acquiring industrial MAS have been identified as one of the main barriers to their adoption. Therefore, establishing cost savings to be achieved by an industrial MAS solution is of paramount importance and is crucial for the acceptance thereof [6]. For this purpose, Multi-Agent Task Allocation (MATA) needs to be optimized with the objective of minimizing the operating costs (mainly electrical energy consumption). However, the problem of optimizing MATA is however a challenging problem due to its non-deterministic polynomial (NP) nature. Most well-known schemes to solve the problem fall under one of two categories: Market-Based and Optimization-Based approaches.

Another major change occuring to the industrial sector associated with I4.0 is the increased adoption of Demand Response (DR) programs. DR programs were enabled by Smart Grid (SG) technologies, and their main objective is to make energy consumers adapt their consumption behaviour according to the electricity supply and market conditions. In price-based DR, this is achieved through time-varying electricity prices to which the consumers respond accordingly, shifting their consumption from peak-load hours to off-peak hours. This increases the overall efficiency of the system, and provides economic benfits to all electricity market participants [7]. Given that electricity consumption is a major cost associated with industrial MAS, it is crucial to consider the implementation of DR programs when formulating the MATA optimization problem, which is often overlooked [8], [9].

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B. Contributions

The main contributions of this study are listed below:

- A market-based approach for optimizing task allocation in a MAS is developed and implemented with the objective of minimizing the overall cost of the system.
- The effect of a price-based DR program is incorporated by considering varying time-of-use (ToU) rates.
- The scalability of the proposed approach is investigated by using four different case studies corresponding to varying numbers of agents/tasks and operating area.

C. Paper Organization

The remainder of this manuscript is organized as follows: Section II presents a survey of the State-of-the-Art literature which considered DR implementation for similar industrial scheduling problems is presented, in addition to studies on MATA applied across various fields of research. In Section III, the problem formulation and the proposed algorithm are presented . Section IV illustrates the performance metrics and the selected scenarios for the case studies. The results and discussion are presented in section V. Finally, Section VI presents the conclusion and recommendations for future work.

II. Literature Review

A. Industrial Scheduling with Demand Response Programs

In [8], varying time-of-use (ToU) electricity rates resulting from industrial DR program participation were modeled for manufacturing systems. Monotonicity analysis was used to determine the effect of modelling parameter on the electricity cost. The developed model was applied to different generic case studies. The results showed that adopting ToU rates can provide cost savings of up to 24.8% per product, given that adequate scheduling of electricity consumption is made accordingly.

In [10], a multi-objective optimization model was presented which considered real-time electricity pricing resulting from industrial DR program participation to schedule job processing, machine idle modes, and human workers. The effect of time-varying electirity prices was found to have a significant effect on the results, with trade-offs necessary between labor and energy costs.

In [11], it is established that the two major costs in industrial sector are labor and electricity costs and that with automation, the latter becomes more significant. The study compares the effect of adopting flat, ToU, and critical-peak pricing (CPP) rates (the latter two corresponding to DR program participation). The study identified the great potential of time-varying electricity rates to promote cost savings provided adequate scheduling is performed. Moreoever, real-time pricing schemes were suggested to have possibly greater potential, albeit associate with higher complexity in modeling in task allocation problems. Therefore, ToU was identified to have a good trade-off between both rates.

B. Optimal Task Allocation in Multi-Agent Systems

In [13], a scalable multi-agent task allocation algorithm has been implemented, motivated by the Material Handling Problem (MHP) in modern warehouses. The MATA problem was modeled as an instance of the Capacity-constrained Vehicle Routing Problem (cVRP). The study presents a heuristic technique called nearest neighbor-based Clustering And Routing (nCAR) and after testing on several scenarios, it proved to have better execution time compared to other available methods.

A combinatorial auction mechanism has been implemented for automated exploration in an unknown terrain task in [14]. Combinatorial auctions differ from single-item auctions in the bidding strategies of the automous vehicles. Synergies between tasks are taken into consideration as the vehicles are set to bid on a bundle of tasks instead of single-task bidding, changing the problem from the widely known single-task and single-agent (ST-SR) to a multi-task and single-agent (MT-SR) assignment problem [15]. Different combinatorial auctioning strategies were studied and compared to each other as well as to the single-item auction bidding strategy.

Swarm intelligence was used for task allocation of a Multi-Agent System (MAS) formed by a group of Unmanned Aerial Vehicles (UAVs) in [16]. A central agent created the tasks whilst MATA was solved using a decentralized approach by the agents themselves. Three complementing algorithms form a new method aiming to maximize performed tasks.

In [17], a comparative study between a market-based approach and an optimization-based approach for MATA was held. The algorithms have been tested on a team of heterogeneous robots and tasks. The results showed that the optimization-based approach outperformed the market-based approach in terms of the best allocation and computation time. Another study [18] addressed the use of MATA for search and rescue missions. A generic market-based approach was proposed and quantitatively evaluated through simulation and real experiments. The results showed high performance and the algorithm's applicability in search and rescue missions.

A resource-based task allocation for MAS was investigated in [19]. Autonomous vehicles monitor their energy levels and they go for the nearest charging station to refill their batteries when their energy levels fall below a certain, predetermined, value. In [20], Contract Net Protocol (CNP) was used to solve the MATA problem using a market-based approach to allocate tasks to automated cleaning vehicles to cooperate for cleaning an area beyond the capabilities of a single unit. Results showed that using the CNP protocol alone is not sufficient to provide acceptable solutions for the MATA problem. In [21], the MATA problem was addressed on a larger scale. The team consisted of self-driving vehicles. The objective was to introduce a hybrid optimization-based approach to solve the problem of multiple intelligent vehicles requests allocation as an instance of MATA problem, to find an optimized solution as per the objective function. A comparative study was conducted between the obtained results and the already available sub-optimal results to validate the proposed approach.

III. METHODOLOGY

Following the conducted literature review, we establish that:

- With increased industrial automation, the MATA problem is an unavoidable one in modern systems, with process scheduling being crucial to maintain cost-efficiency.
- Price-based DR program participation has great potential for reduction of costs in industrial applications.
- ToU rates provide a reasonable trade-off between modeling complexity and cost savings.

It is thus clear that it is important to incorporate ToU rates in MATA problem implementation to manage increased automation in modern industrial applications. As previously mentioned, the MATA problem is very complex to solve due to its NP nature. In order to proceed with obtaining a feasible solution, the problem should be properly formulated by obtaining the governing equations and constraints. In this section, the problem formulation will be discussed along with the algorithm design.

A. Problem Formulation

MATA is a combinatorial search optimization problem. Where a group of m agents $A = \{A_1, A_2, ..., A_m\}$ are to be allocated to a set of n Tasks $T = \{T_1, T_2, ..., T_n\}$. Given the initial locations of the agents and the locations of the tasks, Cost C_{ij} is the cost of agent A_i executing task T_j which is the distance taken by the agent from the current location of the agent A_i to the task T_j. The main objective of the problem is to minimize the total distance travelled by the MAS. Thus, the objective function could be formulated as in equation 1.

$$Cost = \min \sum_{i=1}^{n} C_{ij} \chi_i^j \tag{1}$$

where,

$$\chi_i^j \in \{0, 1\} \ , \forall i \in \{1, ..., n\} \ , \forall j \in \{1, ..., m\} \tag{2}$$

where χ_i^j in (2) represents whether the agent A_j is allocated to task T_i or not.

In this work, the MAS is assumed to consist of a team of mobile agents which will be operating in an automated factory where they interact with human operators to assist them. Hence, they most relocate to the human operators' locations to aid them whenever they are requested to do so.

1) Environment Specifications and Constraints: A map with a known terrain, a predetermined size, and exact obstacle locations is introduced as a binary occupancy grid. A binary occupancy grid is represented as a matrix of zeros and ones. A cell is marked as obstacle free if its value is equal to zero and is marked a an obstacle if the cell value is equal to one. The map is processed and converted to a directed graph to ease up any path planning algorithm for the agent's motion. A directed graph is one type of graphs that deals with each cell in a matrix as an individual component that has some attributes. Each cell is connected with neighboring nodes or cells with a path of a specific distance, forming the distance matrix. In this study, the distance between each cell and its neighboring cell is 1 meter. Diagonal distances are not considered because the agent is not allowed to commute diagonally in the work-space.

2) Agents Attributes: Each agent has a minimum set of attributes that are carefully measured and taken into account for solving the MATA problem. The set of used attributes are:

1) ID number
2) Velocity
3) Current Location
4) Energy Level

All agents are initially deployed with a 100% energy level and discharge with a constant discharge rate that is directly proportional to the total travelled distance by them. The batteries are assumed to last for 5 minutes and charges from 0 to 100 in 1 minute. The cost of charging a 0% to 100% state of charge is assumed to be 1 KWh. Since the MATA algorithm is intended to be generalized, the agents can correspond to a number of industrial actors e.g. mobile machines, robots, etc.

B. Algorithm Design

In solving the MATA problem for optimizing the cost incurred by the MAS for ToU electricity pricing, a robust algorithm is needed to be able to handle most of the cases that might occur whilst solving the problem. The algorithm should monitor the change in the situation of both the map and the agents' status and act accordingly.

The controller cannot handle the expense of solving the whole problem in a single iteration because it will not be able to predict the behavior of the agents and may not consider their updated locations when assigning new tasks to them. Moreover, solving the entire problem only once before the beginning of execution could be computationally exhaustive and migh take a lot of time, which is not desired in a real-time application. Hence, the controller is able to solve the problem by assigning one and only one task to each available agent per iteration. The status of each agent and each task is then checked and based upon the updated information, the next batch of tasks are assigned and so on until there are not any unexecuted tasks left in the market. The detailed algorithm is shown in Algorithm 1.

A map with fixed locations and number of tasks (n), and fixed locations and number of agents (m) is considered. The algorithm begins by assigning all tasks as available and then, it proceeds with the higher level controller. All agents are set to be available. The agents begin submitting bids on the available tasks using the getBids function. Their bids totally depend on the distance between the agent's current position and the task it is trying to win. The bids are calculated using the formula:

$$bid_{ij} = \sum_{i=1}^{n} \sum_{j=1}^{m} d_{ij} \tag{3}$$

The agent's motion is restricted in four unique directions; North, East, South, and West. A Breadth-First Search (BFS) algorithm was used for path planning of the agents inside the environment.

Some agents' energy levels will decline beneath the specified threshold specified by the system. Once this happens, the

Algorithm 1 Market-Based Algorithm

Input Tasks List (T), Agents List (R), Charging Stations (Ch_St), Map Matrix (p), Map Directed Graph (DG)
Output R, T, status summary
Bidding List *bid_List*
Available Tasks *availT*
Available Agents *availR*
Allocation Summary *alloc_summary*
Best Alloc *best_alloc*
$AvailableTasks \leftarrow tasks$
while $!isEmpty(availTasks)$ **do**
  $bid\_list \leftarrow getBids(availR, availT)$
  $alloc\_summ \leftarrow initAlloc(bid\_list, availT, availR)$
  $best\_alloc \leftarrow neg(alloc\_summ, availR, availT)$
  $[R, T, Ch\_St] \leftarrow update(R, T, Ch\_St)$
  $status\_summ \leftarrow report(R, T)$
end while

TABLE I
ENERGY PRICE (EUR/KWH) FOR EACH TOU INTERVAL.

Interval (Hours)	Price (EUR)
12:00 AM - 8:00 AM	0.15 x 1
9:00 AM - 5:00 PM	0.15 x 1.5
6:00 PM - 12:00 AM	0.15 x 1.2

agent with low energy level sets its status to be unavailable and refrain from participating in the next auction round. Instead, it begins moving to the nearest charging station in order to recharge its battery. The agent keeps out of service for one bidding round and returns in the next bidding round when the auctioneer reopens the auction. The process is repeated until all tasks are completed.

IV. Test Scenarios and Performance Metrics

In this section, the executed experiments are shown and explained along with the performance metrics that are going to be measured in order to determine the effect of the task allocation algorithm on the efficiency of the system. In the scenarios, the day is assumed to be divided into three ToU intervals, with varying energy price (EUR/KWh). This is shown in Table I and Figure 1.

A. Case Studies

In order to investigate the scalability of the proposed algorithm, different case studies with various complexities are used for validation. The scenarios are as follows:

1) Small-Scaled Scenario (4 Agents and 10 Tasks)
2) Large-Scaled Scenario (40 Agents and 120 Tasks)

Moreover, these three scenarios were tested on two different maps with different sizes and obstacle locations.

1) Small Map (101×54 m^2)
2) Large Map (200×150 m^2)

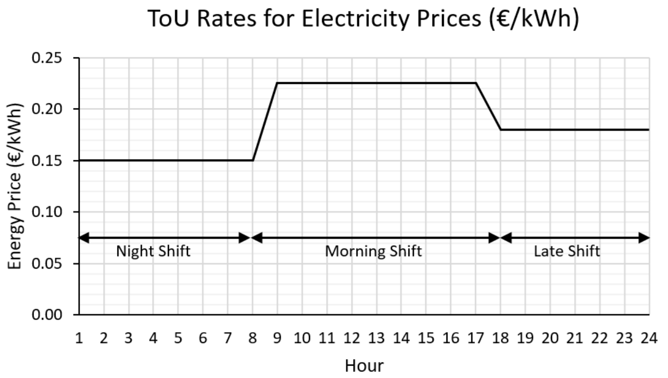

Fig. 1. Varying electricity prices corresponding to ToU during night, morning, and late shifts in an industrial setting.

B. Performance Metrics

The proposed algorithm is evaluated by means of three main performance metrics:

1) Distance Travelled by the MAS
2) Cost incurred by the MAS in EUR
3) Computational Time

The algorithm is compared against random assignment task allocation in order to evaluate its effectiveness in terms of cost reduction and computational effort.

V. Results and Discussion

In this section, the algorithm is tested on the proposed scenarios in IV in both, small and large scaled, maps resulting in a total of four case studies. The testing environment is shown along with the obtained results in terms of the mentioned performance metrics.

A. Testing Environment

All simulations were carried out on a standard computer (Intel ”Sandy Bridge” generation, i5 processor with dual core and 8GB memory). The simulations were tested on MATLAB R2016a software.

B. Simulations and Results

The results of the small and large maps are presented with the cost in EUR calculated based upon equation 4 and using the rates provided in table I and the fact that one complete charge costs 1 KWh as mentioned in Section III

$$Cost_{EUR} = Charge\_Consumed\_in\_KWh \times Price \quad (4)$$

All results are based on taking the average of running the algorithm with the same starting locations of the agents and tasks for 20 times. The results are shown in tables II, III, IV and V. Tables II and III and Figure 2 refer to results obtained from the small map; while Tables IV and V and Figure 3 refer to results obtained from the large map.

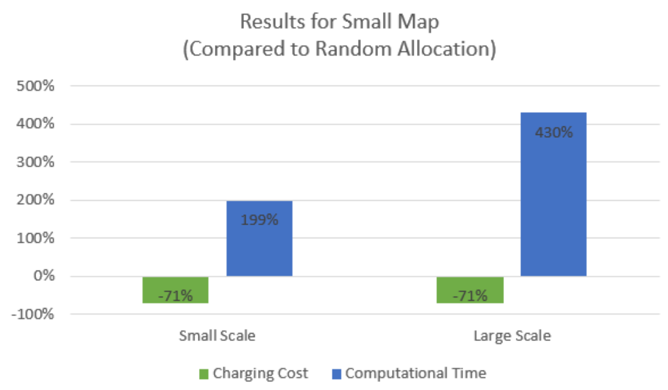

Fig. 2. A comparison between the small and large scale scenarios in terms of change in charging cost and computational time (relative to random task allocation) in the small map.

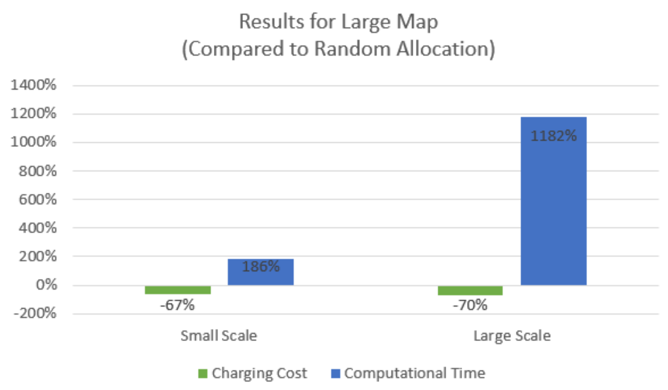

Fig. 3. A comparison between the small and large scale scenarios in terms of change in charging cost and computational time (relative to random task allocation) in the large map.

TABLE II
SMALL SCALE - SMALL MAP

Used Algorithm for solving the MATA problem	Distance Travelled by the MAS (meters)	Charging Cost (EUR)	Computational Time (seconds)
Random Assignment	426	17.1	0.083
Market-Based Approach	207	5.04	0.165

TABLE III
LARGE SCALE - SMALL MAP

Used Algorithm for solving the MATA problem	Distance Travelled by the MAS (meters)	Charging Cost (EUR)	Computational Time (seconds)
Random Assignment	989	167.3	0.13
Market-Based Approach	336	48.6	0.56

TABLE IV
SMALL SCALE - LARGE MAP

Used Algorithm for solving the MATA problem	Distance Travelled by the MAS (meters)	Charging Cost (EUR)	Computational Time (seconds)
Random Assignment	2089	654.6	0.492
Market-Based Approach	713	217.9	0.913

TABLE V
LARGE SCALE - LARGE MAP

Used Algorithm for solving the MATA problem	Distance Travelled by the MAS (meters)	Charging Cost (EUR)	Computational Time (seconds)
Random Assignment	3691	1365.7	0.492
Market-Based Approach	1522	413.9	5.816

C. Discussion

It is shown from the obtained results that the proposed Market-Based Approach highly contributes in decreasing the cost incurred by the agents (between 67% and 71% decrease in costs in all case studies). The agents also traveled less distance (almost 3 times less) when compared to random task allocation. This, in turn, allows the agent to work more and charge less in the high price interval which eventually leads to having the agents charge in the less expensive interval of the day. This leads to reduced costs of charging which is an important aspect that reflects on the overall system efficiency.

By comparing Figures 2 and 3 it can be seen that while the scalibility of the algorithm is acceptable with respect to the problem scale (number of agents and tasks), it is not so with respect to the map size. In the case of the small map, the same 71% cost reduction was obtained for the large scale problem, but the computational effort increased from 199% to 430% compred to random allocation. Meanwhile, for the large map, the cost reduction improved by a mere 3 % while the computational efficiency was more than 6 times worse when the problem scale was increased. Therefore, the scalability is clearly more sensitive to the map size than the number of agents or tasks.

VI. CONCLUSIONS AND FUTURE WORK

This study proposed and tested a Market-Based Approach to solve MATA for industrial applications considering the presence of a price-based DR program with difference ToU electricity prices. By applying the proposed method on different case studies, it was found that the proposed MATA approach resulted in a cost reduction of 67-71 % compared to random allocation. A sensitivity analysis was performed using different case studies to determine the scalability of the model with respect to the number of agents, number of tasks, and map size. The scalability analysis suggests that the proposed algorithm is significantly less sensitive to the number of agents and tasks than it is to the map size. Therefore, a comparison against the use of meta-heuristic approaches is recommended for future work. In addition, heterogeneous system of agents and tasks should be considered to improve the realism of the case studies.

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REFERENCES

[1] Hermann, M.; Pentek, T.; Otto, B. Design Principles for Industrie 4.0 Scenarios. Proc. Annu. Hawaii Int. Conf. Syst. Sci. 2016, 2016-March, 3928–3937. https://doi.org/10.1109/HICSS.2016.488.

[2] Wang, S., Wan, J., Zhang, D., Li, D. and Zhang, C., 2016. Towards smart factory for industry 4.0: a self-organized multi-agent system with big data based feedback and coordination. Computer Networks, 101, pp.158-168.

[3] Singh, R., Samkaria, R., Gehlot, A. and Choudhary, S., 2018. Design and Development of IoT enabled Multi Robot System for Search and Rescue Mission.

[4] Ma, H., Wu, X., Gong, Y., Cui, Y. and Song, J., 2015, October. A task-grouped approach for the multi-robot task allocation of warehouse system. In Computer Science and Mechanical Automation (CSMA), 2015 International Conference on (pp. 277-280). IEEE.

[5] Ovalle, A.; Hably, A.; Bacha, S.; Ramos, G.; Hossain, J. M. Escort Evolutionary Game Dynamics Approach for Integral Load Management of Electric Vehicle Fleets. IEEE Trans. Ind. Electron. 2017, 64 (2), 1358–1369. https://doi.org/10.1109/TIE.2016.2615042.

[6] Karnouskos, S.; Leitao, P. Key Contributing Factors to the Acceptance of Agents in Industrial Environments. IEEE Trans. Ind. Informatics 2017, 13 (2), 696–703. https://doi.org/10.1109/TII.2016.2607148.

[7] Paterakis, N. G.; Erdinç, O.; Catalão, J. P. S. An Overview of Demand Response: Key-Elements and International Experience. Renew. Sustain. Energy Rev. 2017, 69 (November 2016), 871–891. https://doi.org/10.1016/j.rser.2016.11.167.

[8] Wang, Y.; Li, L. Time-of-Use Based Electricity Cost of Manufacturing Systems: Modeling and Monotonicity Analysis. Int. J. Prod. Econ. 2014, 156, 246–259. https://doi.org/10.1016/j.ijpe.2014.06.015.

[9] Gong, X.; Liu, Y.; Lohse, N.; De Pessemier, T.; Martens, L.; Joseph, W. Energy- and Labor-Aware Production Scheduling for Industrial Demand Response Using Adaptive Multiobjective Memetic Algorithm. IEEE Trans. Ind. Informatics 2019, 15 (2), 942–953. https://doi.org/10.1109/TII.2018.2839645.

[20] Liekna, A., Lavendelis, E. and Grabovskis, A., 2012. Experimental analysis of contract net protocol in multi-robot task allocation. Applied Computer Systems, 13(1), pp.6-14.

[10] Gong, X.; Liu, Y.; Lohse, N.; De Pessemier, T.; Martens, L.; Joseph, W. Energy- and Labor-Aware Production Scheduling for Industrial Demand Response Using Adaptive Multiobjective Memetic Algorithm. IEEE Trans. Ind. Informatics 2019, 15 (2), 942–953. https://doi.org/10.1109/TII.2018.2839645.

[11] Wang, Y.; Li, L. Manufacturing Profit Maximization under Time-Varying Electricity and Labor Pricing. Comput. Ind. Eng. 2017, 104, 23–34. https://doi.org/10.1016/j.cie.2016.12.011.

[12] Badreldin, M., Hussein, A. and Khamis, A., 2013. A comparative study between optimization and market-based approaches to multi-robot task allocation. Advances in Artificial Intelligence, 2013, p.12.

[13] Sarkar, C., Paul, H.S. and Pal, A., 2018, May. A scalable multi-robot task allocation algorithm. In 2018 IEEE International Conference on Robotics and Automation (ICRA) (pp. 1-9). IEEE.

[14] Berhault, M., Huang, H., Keskinocak, P., Koenig, S., Elmaghraby, W., Griffin, P. and Kleywegt, A., 2003, October. Robot exploration with combinatorial auctions. In Proceedings 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003)(Cat. No. 03CH37453) (Vol. 2, pp. 1957-1962). IEEE.

[15] Khamis, A., Hussein, A. and Elmogy, A., 2015. Multi-robot task allocation: A review of the state-of-the-art. In Cooperative Robots and Sensor Networks 2015 (pp. 31-51). Springer, Cham.

[16] Schwarzrock, J., Zacarias, I., Bazzan, A.L., de Araujo Fernandes, R.Q., Moreira, L.H. and de Freitas, E.P., 2018. Solving task allocation problem in multi Unmanned Aerial Vehicles systems using Swarm intelligence. Engineering Applications of Artificial Intelligence, 72, pp.10-20.

[17] Hussein, A. and Khamis, A., 2013, December. Market-based approach to multi-robot task allocation. In Individual and Collective Behaviors in Robotics (ICBR), 2013 International Conference on (pp. 69-74). IEEE.

[18] Hussein, A., Adel, M., Bakr, M., Shehata, O.M. and Khamis, A., 2014. Multi-robot task allocation for search and rescue missions. In Journal of Physics: Conference Series (Vol. 570, No. 5, p. 052006). IOP Publishing.

[19] Lee, D.H., 2018. Resource-based task allocation for multi-robot systems. Robotics and Autonomous Systems, 103, pp.151-161.

[21] Hussein, A., Marín-Plaza, P., García, F. and Armingol, J.M., 2018. Hybrid Optimization-Based Approach for Multiple Intelligent Vehicles Requests Allocation. Journal of Advanced Transportation, 2018.