Improved Decentral Task Allocation for Autonomous Guided Vehicle Systems based on Karis Pro

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Keywords—Task Allocation; AGV; Karis Pro

Abstract—**In this paper, we extended an existing decentralised method for allocating tasks to AGVs, by additionally considering vehicles which already are assigned to a task. This was achieved by also considering the opportunity costs arising from a vehicle passing a current task to another vehicle and subsequently accepting a new task. This loosened restriction is enabling the vehicle fleet for a higher flexibility, which can be used for improving the efficiency of the overall system. By means of simulation, our findings confirm the notion that our extended method – namely Karis Pro+ (KP+) – leads to lower traffic density and higher flexibility, both of which are important KPIs for large-scale transport vehicle systems.**

List of Abbreviations

AGV Automated Guided Vehicle
BMBF Bundesministerium für Bildung und Forschung (English: German Federal Ministry of Education and Research)
FCFS first-come-first-serve
KIT Karsruhe Institute of Technology
KP Karis Pro
KP+ Karis Pro+
KPI Key Performance Indicator
MRPD Multi-robot Task Allocation for Pickup and Delivery
MRS Multi-robot System
MRTA Multi-robot Task Allocation
TeSSI Temporal Sequential Single-item Auction
V_I idle vehicles
V_P vehicles in pickup
V_D vehicles in delivery
R_A assigned transportation requests
R_U unassigned transportation requests

I. Introduction

Greater efficiency, higher productivity and more flexibility are some of the key objectives that govern today's production operations (Dorri et al. 2018). Consequently, these objectives are the focus of strategic efforts regardless of company's industrial branch. Production and logistics have been identified as the two areas in manufacturing companies that are especially subject to meet these demands, which entails the necessity for continuous innovation and improvements (Dorri et al. 2018). The main driving forces behind these objectives and the associated requirements are the competitive pressure of the market as well as customer demands for greater customisation and individualisation (Leupold et al. 2018; Jazdi 2014). In order to meet these requirements and to maintain a competitive edge in its industry, new technologies for handling material are in demand. Conventional material flow systems, seemingly rigid in terms of layout and throughput, are therefore continuously becoming less suitable to meet industry standards. The constantly rising demand for flexibility drives the development of autonomous floor-bound vehicle systems. One of these vehicle systems is the result of the research project Karis Pro, introduced by Colling et al. (2016) as a "modular, decentralised controlled automated guided vehicle system". This task allocation system harnesses both, a decentralised job creation system and a decentralised job allocation system. Due to its flexible application, the developers state this system can be employed with ease by the customer and without the need for infrastructural adjustments. The decentralised control and the autonomous nature of each vehicle forms a reliable system that caters to the requirements of modern industrial processes (Colling et al. 2016).

Karis Pro (KP) has been utilised in two industrial settings under real-life conditions. An industrial pilot study, set in the production lines, was successfully performed in corporation with Bosch and Audi (see Figure 1). The use cases of autonomous transport systems in this environment are driven by the principles of lean production, in order to reduce the produced and transported lot sizes as well as to increase the frequency of arrivals and departures without having to increase the number of required personnel (Trenkle 2016).

Particularly large-scale vehicle systems depend on highly efficient organisation to avoid traffic jams and delays (Versteegt and Verbraeck 2002). A means of achieving this may be to allocate scarce resources, such as the number of available vehicles, as efficiently as possible. Our developed method aims to improve the established method of Colling et al. (2016) to enhance the performance and efficiency significantly.

This paper is divided into the following sections. Section II provides a review of the relevant literature, followed by an introduction of the extended version of Karis Pro, namely Karis Pro+ and an outline of the associated development ratio-

Fig. 1. Karis Pro AGV in an Industrial Use Case; Illustration from amplify.pepperl-fuchs.com/de/inhalte/121/wo-die-dinge-ins-schwaermen-geraten

nale. A description of a subsequent simulation study to validate the improvements in Section IV precedes the conclusion in Section V.

II. Related Literature

In academia, the issue of task allocation to agents is known as the *Multi-robot Task Allocation* (MRTA) problem or, more specific to the use-case of this study, the *Multi-robot Task Allocation for Pickup and Delivery* (MRPD) problem. The MRPD defines an extension of the widely studied MRTA problem which assumes each task as a single location to visit (Heap and Pagnucco 2013). By definition, a *Multi-robot System* (MRS) describes a group of agents that are assigned to perform a collective behaviour (Khamis, Hussein, et al. 2015). Due to its high industrial academic relevance, one of the major topics of research in the area is the multi-robot task allocation problem. That is the problem of dividing tasks across robots so that some objective of interest is optimised (Nunes, Manner, et al. 2017). Referring to Gerkey and Matarić (2004), this particular MRPD problem can be described as ST-SR-IA (single-task robots, single-robot tasks, instantaneous assignment).

Contributions around MRTA are utilised in many different industries, such as for fleets of cooperated unmanned aerial vehicles (Moon et al. 2015; Bellingham et al. 2003; Innocenti et al. 2010), maritime industry (Bădică et al. 2018), manufacturing automation (McIntire et al. 2016), robots for refinery inspections (Liu and Kroll 2012) and areas where it is either too expensive or dangerous for humans to work (Nagarajan and Thondiyath 2013; Khamis and ElGindy 2012). In order to find a suitable solution for the task allocation problem, the literature proposes several different concepts. The review of the literature indicates that the most used and state-of-the-art solution for a large-scale decentralised system in order to achieve satisfactory performance is the agent-based auction mechanism. Auctions, in any form, have been used in societies throughout history to allocate scarce resources among interested parties (Gerkey and Matarić 2002). Consequently, auctions have received a great deal of attention from economists, and a rich body of theory exists regarding their properties, especially their ability to deal with uncertainty (Akerlof 1970; Holt 1979).

For common industrial applications, agents such as robots or vehicles, bids on tasks by calculating the amount of effort needed to perform them. In most cases, the effort depends on the distance between the agent location and the task location plus any additional cost for doing the task itself, such as resources consumed (e. g. time spent) in doing the task (Nunes and Gini 2015). The agents act as bidders and stations as sellers. Thereupon, the agents submit their bids and, depending on this, receive an acceptance or refusal (Schwarz et al. 2013).

The smart coordination of groups of robots is an important topic in this context, as significant amount of resources can be saved when robots work together. While this does not necessarily mean that the robots conduct their tasks together in teams, but they do adjust their actions to each other (Gerkey and Matarić 2002).

One should also pay attention to spatial and temporal constraints, as many tasks have to be executed in a specified time window in industrial practice, as well. For this reason, the *Temporal Sequential Single-item Auction* (TeSSI) algorithm was developed (Nunes and Gini 2015; Nunes, Manner, et al. 2017). In addition, Bădică et al. (2018) proposed an "intelligent" freight broker agent which uses a mathematical optimisation service to compute the optimal schedule of vehicles fulfilling customer requirements.

Using heuristic-based task allocation algorithms is another strategy to solve such a task allocation problem (Jennings et al. 2001; Windelinckx and Strens 2004; Nagarajan and Thondiyath 2013). Such static approaches usually require that the announced tasks and the available vehicles are known prior to the actual calculation and scheduling phase. As this is not the case for a decentralised control setting, these approaches are of no interest for this research (Schwarz 2014).

Summarised, agent-based methods like negotiations (e. g. auctions) are an appropriate and established method for proactive allocation of tasks to vehicles (Lagoudakis et al. 2004; Tovey et al. 2005). One showcase project for a decentral task allocation will be presented in detail in the next section. Furthermore, Karis Pro will be enabled for the idea of different traveller assignment strategies, presented by Hyland and Mahmassani (2018).

III. Karis Pro and the Traveller Assignment Strategies

Karis Pro is a research project of the Karsruhe Institute of Technology (KIT), which was carried out between 2013 and 2016 with the support of the German Federal Ministry of Education and Research (BMBF).

As opposed to the centralised methods, the process of allocating tasks to vehicles within the Karis Pro system takes place without the involvement of a central control unit. Instead, the vehicles carry out auctions in order to determine which vehicle should handle which task (Trenkle 2016). After a task is generated, it is automatically entered into a list that ranks all tasks according to a specific priority. The tasks with the highest priority can be found at the top of the list. As Colling et al. (2016) has not specified which priority was used in their approach, different criteria for the priority rule could be selected depending on the underlying specifications. Possible examples of these priorities are:

- Date of task generation, i. e. according to the first-come, first-served rule, the oldest tasks have the highest priority
- Deadline when a task has to be fulfilled, i. e. tasks closer to the deadline have a higher priority
- Distance between origin (source) and destination (sink), i. e. shorter distances have a higher priority or vice versa
- Pre-determined rules, i. e. certain source-sink relations are more critical and have thus a higher priority

The tasks are assigned to vehicles just before their execution, which means that each vehicle receives only one task at a time. The task allocation process begins when one of two events takes place. Either a vehicle has just finished its task and there are tasks left on the list, or a vehicle is idle and a new task appears on the list. In both instances the vehicle chooses the task with the highest priority and begins the auction process. During the first step of the auction, the vehicle that started the auction calculates its own bid. Subsequently, it contacts all other vehicles and asks them to submit their bids. These vehicles can be categorised as follows:

1) *Idle*: Without a task
2) *Pickup*: Vehicle is currently driving to a source to pick up a task. This can also be described as an "empty drive" as it is not adding value
3) *Delivery*, without reservation: Vehicle is currently transporting a task to its sink and is not reserved for a subsequent task.
4) *Delivery*, with reservation: Vehicle is currently transporting a task to its sink and is reserved for a subsequent task.

Under the constraints of Karis Pro, vehicles from Category 1 (*Idle*) and Category 3 (*Delivery*, without reservation) will respond with a bid to the auctioning vehicle. The bid itself is given in number of seconds and is either appraised or calculated by adding the following values:

1) The expected remaining time required to fulfil the current task (only for vehicles of Category 3)
2) The expected time to reach the source of the new task (for vehicles of Categories 1 and 3)

Therefore, the bid is the amount of time it would take each vehicle to reach the source of the new task. After having received all bids, the auctioning vehicle determines the most efficient vehicle, which can lead to either one of two outcomes. The vehicle itself is the most suitable for the task (i. e. the lowest bid) or another vehicle is more favourable. In the first case, the auctioning vehicle immediately begins to execute the task and informs the other vehicles that it was awarded with the task. In the second case, the auctioning vehicle informs the winner that it has won the auction. Subsequently, it chooses the next task on the list and commences a new auction. The auctioning vehicle continues to repeat the auctioning process until it either wins an auction, there are no more tasks left on the list or no other vehicles remain to participate in auctions.

The upcoming presented contribution deals with assignment strategies, which are a substantial part of task allocation methods (Nunes, Manner, et al. 2017). Hyland and Mahmassani (2018) have compared different assignment strategies for a share-use autonomous vehicle mobility service. In this setting, the vehicles are controlled by a central unit. This information

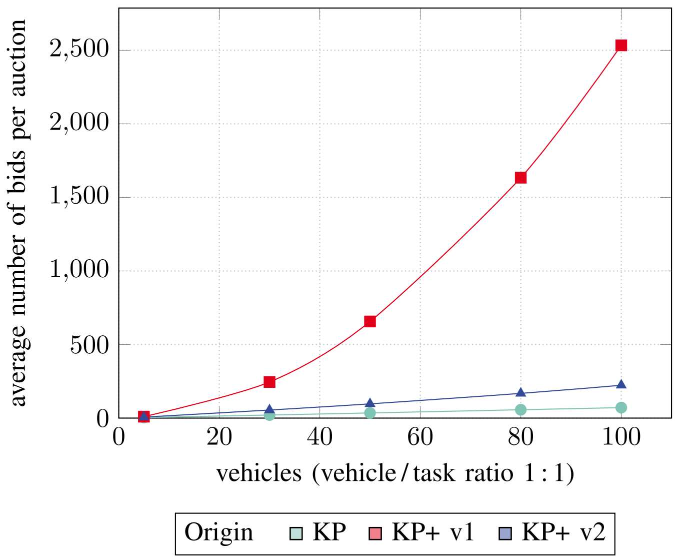

Fig. 2. Average Number of Bids per Auction (5,000 Samples)

hub provides a direct origin-to-destination service to travellers who request a ride, or, if one were to apply this to the environment of our research, for a source-to-sink service of a load carrier.

Table I summarises the different strategies compared by Hyland and Mahmassani (2018). The first two assignment strategies are basic first-come-first-serve (FCFS) strategies with different objectives, to either minimise waiting time or travelling distance. Here, unassigned travellers (R_U) are assigned to idle vehicles (V_I). The other four optimisation strategies consider different combinations of idle vehicles, vehicles in pickup (V_P) and vehicles in delivery (V_D) as well as the variables unassigned or assigned travellers (R_A). In order to generate the most efficient outcome in light of the given objectives, a mathematical solver is used to identify the most suitable allocation. The optimisation-based strategies, especially those that involve the reassignment of already assigned travellers (R_A), significantly outperform both FCFS assignment strategies.

More specifically, the results of their simulation study indicate that Strategy 6 unambiguously outperforms all other strategies in terms of empty fleet miles in all of the examined scenarios. In terms of traveller waiting times, Strategy 6 is deemed to be more efficient when the fleet size is small relative to the demand rate. For large fleet sizes like 200+ vehicles, Strategy 3 and Strategy 4 outperform Strategy 5 and Strategy 6 in terms of traveller waiting times. It is proposed that Strategy 5 in Table I corresponds to the current Karis Pro method.

IV. Methodology

The basic methodology to achieve this research's objective, is to compare the existing method of Colling et al. (2016) with our extended version, namely *Karis Pro+*. This comparison is accomplished by means of a simulation study in which the agent-based modelling paradigm is used.

The software *AnyLogic* is chosen for this purpose, as it supports the paradigms of agent-based modelling and thus

TABLE I. OVERVIEW OF TRAVELLER ASSIGNMENT STRATEGIES (HYLAND AND MAHMASSANI 2018)

	Strategy	Travelers (R')	Vehicles (V')	Sequential/Simultaneous	Traveler Reassignment?	En-Route Drop-off
1	First-Come-Frist-Serve	R_U	V_I	Sequential	No	No
2	First-Come-First-Serve	R_U	V_I	Sequential	No	No
3	Optimization	R_U	V_I	Simultaneous	No	No
4	Optimization	$R_U \cup R_A$	$V_I \cup V_P$	Simultaneous	Yes	No
5	Optimization	R_U	$V_I \cup V_D$	Simultaneous	No	Yes
6	Optimization	$R_U \cup R_A$	$V_I \cup V_P \cup V_D$	Simultaneous	Yes	Yes

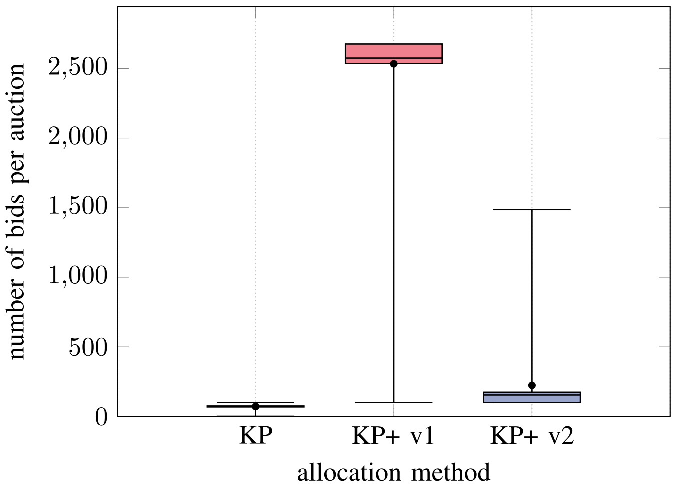

Fig. 3. Bid Requests for a large-scale Scenario of 100 Vehicles / 100 Tasks (5.000 Samples)

the architecture of a multi-agent system. With its ability to combine several simulation methods (*discrete-event*, *agent-based* and *system dynamics*), it fulfils, as the only software that features multi-method simulation modelling, the basic pre-requisites for this research project. A combination of *discrete-event* and *agent-based* methods is proposed for the simulation study, as the performance of both methods can be examined in a risk-free environment.

The limitations of *AnyLogic* are of a general nature. As the software is proprietary and not open-source, the project depended on the provision by the *AnyLogic Company*. Furthermore, the project is bound to *Java* implementations for database applications or extensions (e. g. algorithms or model implementations). It is unlikely that either of these limitations will influence the feasibility of this project. General limitations that apply to the discrete-event simulation and agent-based modelling, relate to the level of detail with which the simulation is constructed (Mes et al. 2008; Heger and Voss 2018).

V. DRAFT OF KARIS PRO+

Motivated by the informative simulation study of Hyland and Mahmassani (2018), our goal was to extend the Karis Pro task allocation method by permitting the reassignment of already allocated tasks. That is, vehicles that are currently driving to collect a load have to be able to diverge towards a new task and pass the one currently assigned to another vehicle to ensure that this task won't be late or forgotten. Also, vehicles already carrying a load have to be able to change their reservation for the subsequent task if this is beneficial for the objective in the overall system.

The main difficulty is the decision when to reallocate an already assigned, but not initiated, task on to another vehicle, while allocating the new task to the formerly assigned vehicle so that the overall system benefits from this change. For this purpose, it is important to determine the opportunity costs, the costs accrued due to a reallocation, from an overall perspective. These costs in combination with the potential effort, more specifically time or distance a vehicle needs to travel, are used to formulate a key performance indicator to support the decision-making process.

A. *Opportunity Costs*

Opportunity costs have to be considered whenever a vehicle has to pass an assigned task on to another vehicle. In our case, two potential outcomes may arise when a new task is auctioned and is subsequently assigned to one of the following vehicles:

1) A vehicle which is currently driving to pick up its assigned task (*pick up task*). This *pick up task* can be passed on to another vehicle and is then substituted by the new task.
2) A vehicle with a loaded task (*delivery task*) and a subsequent reservation (*reservation task*). Here, the *reservation task* can be passed on to another vehicle.

Due to the decentralised organisation, an increased flow of information is required between the vehicles in order to determine the opportunity costs: A vehicle, that intends to determine the opportunity costs of a currently assigned task, has to query all other vehicles for bids in an effort to determine which vehicle is going to perform the task. Due to the nature of this process, the process chain may well end in an infinity loop. That is, in order to ascertain these costs, the query is going to include vehicles that also have to calculate opportunity costs and therefore also have to query other vehicles. At this point, it is necessary to include only those vehicles in the calculation of opportunity costs that can provide an answer without again considering opportunity costs, i. e. vehicles in an idle state or a delivery state without reservations. Figure 2 shows the resulting bids of Version 1 of Karis Pro+ in red. The method can therefore be classified as not scalable (Lirkov and Margenov 2018). More than 1,600 bid calculations per tasks are required in a system with 80 vehicles in the system, in some cases even more.

Consequent to the primary feasibility assessment of Version 1 of Karis Pro+ described above, KP+ was adapted

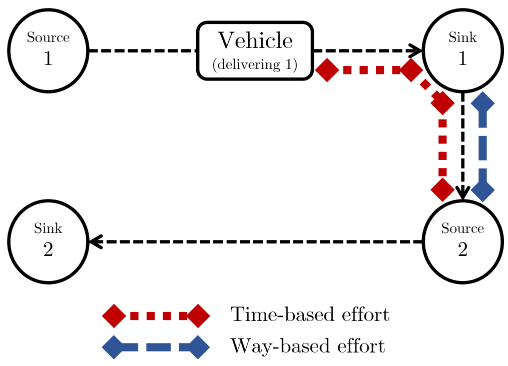

Fig. 4. Illustration of the time-based and the way-based Calculation of Effort

TABLE II. COMPOSITION OF BIDS REGARDING NEW TASKS AND CURRENT TASK'S PRIORITY

Priority: New Mission (auction)	Priority: Current Mission (pickup / delivery with reservation)	Bid Composition
✔	✘	Only own Effort (time-based)
✘	✘	Own Effort + Opportunity Costs (both way-based)
✔	✔	Own Effort + Opportunity Costs (both time-based)
✘	✔	No bid calculated

to Version 2 in order to reduce the number of necessary bid calculations. In Version 2 the opportunity costs are only determined if the best bidder has to determine the opportunity costs to establish the total costs for the system, i. e. *pickup* mode or *delivery* mode with *no reservation*. The reduction of the number of bid calculations from and KP+ v1 to KP+ v2 are substantial as is illustrated in Figure 2 and Figure 3.

B. Priorities and Calculation of Effort

In the following simulation study, which was performed as a case study in the automotive sector, schedules play an important role. To ensure that all tasks are delivered on time, while utilising the temporal flexibility of each task in the planning process, Karis Pro+ operates with two types of priorities (*priority* and *no priority*). Whenever a task is in danger of being delayed, it will receive a priority flag, which will position it on the first ranks of the task list.

Furthermore, the calculation of the effort required for a vehicle to fulfil a specific task depends on its priority status. That is, all calculations for priority tasks are time-based, whereas the effort for no priority tasks is based on the distance a vehicle has to travel. This important differentiation ensures that priority tasks will be performed as fast as possible regardless of the distance it would need to travel. Both calculation methods are depicted in Figure 4. The time-based effort is measured in seconds from the present to the estimated time of arrival at the new task source (*Source 2* of Figure 4). However, the way-based effort is measured in meters from the current task's sink (*Sink 1*) to the new task's source (*Source 2*). Both calculation methods ensure that tasks *without priority* are delivered with the least traffic possible and tasks *with priority* as fast as possible.

Depending on this priority setting, each vehicle calculates its own effort in seconds or meters and – if requested – the opportunity costs. Table II illustrates the bid composition for different priority combinations for the newly auctioned task and the currently assigned task of the vehicle.

VI. SIMULATION STUDY

The following section describes the simulation study, which was carried out to compare the performance of KP and KP+. The software *AnyLogic* version 8.6, was used to model the environment and all processes. In the upcoming subsections, the simulation setup, the parameters and the results will be presented in detail.

A. Setup and Parameters

Tasks were carried out by a predetermined number of vehicles. All vehicles were positioned at an initial location at a random point beside the road network, also referred to as fit-point. Tasks appeared at random fit-points, however parameters were set to avoid clustering of such. Each task was assigned to a sink at a random free fit-point with a minimum linear distance of ⅓ of the total layout dimensions. The total number of tasks in the system was also limited by the parameter *Task Pool* for each simulation run. Therefore, whenever a task was completed, a new task appeared at another random fit-point. This logic ensured a constant utilisation of the vehicles, adjustable by the ratio between two parameters: *number of vehicles* and *size task pool*. When a task appeared, a random deadline between 20 and 30 minutes was set. This parameter was chosen to have a meaningful pressure on the system. Seven minutes prior to this deadline, a task was prioritised if had not already been collected by a vehicle. Priority tasks were collected by the closest vehicle and not, as is the case for non-prioritised tasks, by the vehicle with the least way–based effort. This parameter was chosen through preliminary studies in the same layout and ensures that tasks are not delayed.

B. Scenarios

The study compares the Karis Pro and Karis Pro+ methods in scenarios incorporating a variety of scale and utilisation levels. We selected scenarios with 5, 30, 80 and 100 vehicles, thus providing differing scale levels and combined these with differently sized task pools to generate varying load factors. Three alternative task pools were chosen and applied to each vehicle pool size: one with the same number of tasks as number of vehicles, one with 20 % fewer and one with 20 % more tasks than vehicles. Each described scenario was calculated with both methods KP and KP+ and 5,000 tasks.

C. Results and Discussion

The results of the simulation study are presented in the following section. The statistics are utilised to compare the task allocation methods Karis Pro and Karis Pro+ for the differently scaled scenarios.

Figure 5 illustrates the average utilisation for both allocation methods and the three different workload ratios. A vehicle is said to be utilised when it is either collecting a load or delivering a load. For all scenarios, KP+ has a lower utilisation than KP. No tasks were delayed, and all requirements were met in all of the scenarios. The lower utilisation rate can be explained by the fact that KP+ allocates tasks in advance. That is, vehicles already underway can be scheduled for a subsequent task, instead of activating an idle vehicle which would be associated with greater effort.

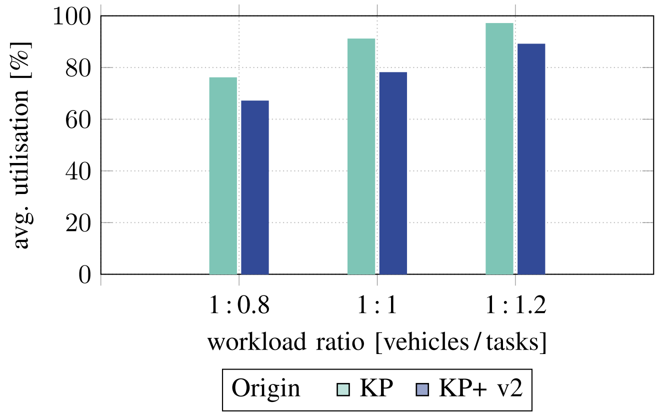

Fig. 5. Average Utilisation for each Workload and Allocation Method

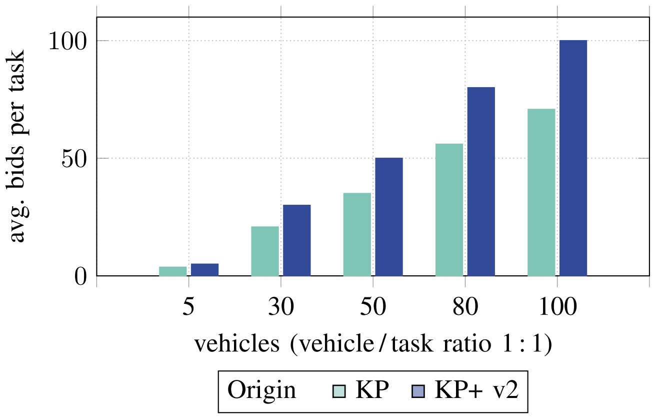

Fig. 6. Average Bids per Task for a Vehicle / Task Ratio of 1 : 1 (5,000 Samples)

Corresponding with the lower utilisation of KP+, the throughput, given in tasks per hour, is also lower for KP+ than KP (see Figure 7). As all requirements are met in all KP+ scenarios, this finding can deem to be of secondary importance. KP+ makes use of the temporal flexibility of each task's deadline to execute it with the least necessary effort in terms of meters travelled per task. This finding is represented in Figure 8. The original KP method has a significant higher way-based effort to process tasks than KP+ (between 7 % and 23 %).

The required communication effort, represented by bid requests per task, was also evaluated. It might seem self-evident that KP+ should require more communication between the vehicles than KP, since vehicles bid in every mode and not only in *idle* or *delivery* mode. For a vehicle / task ratio of 1 : 1, the communication effort is illustrated in Figure 6.

VII. Conclusion

Motivated by the contribution from Hyland and Mahmassani (2018), this study has introduced an alternative decentralised task allocation method based on Karis Pro (Colling et al. 2016), which has been proven to be superior, namely Karis Pro+. When auctioning a task, this version also considers vehicles that are either already performing a task or are reserved as a potential resource for a subsequent one. The aim of this study was to determinate opportunity costs for the overall system and use them to make better decisions for reaching the objective. By using the same bidding system as Karis Pro, every vehicle is able calculate the effort required for passing a task on to another vehicle. This feature improves the flexibility of the system by a substantial margin. The presented simulation

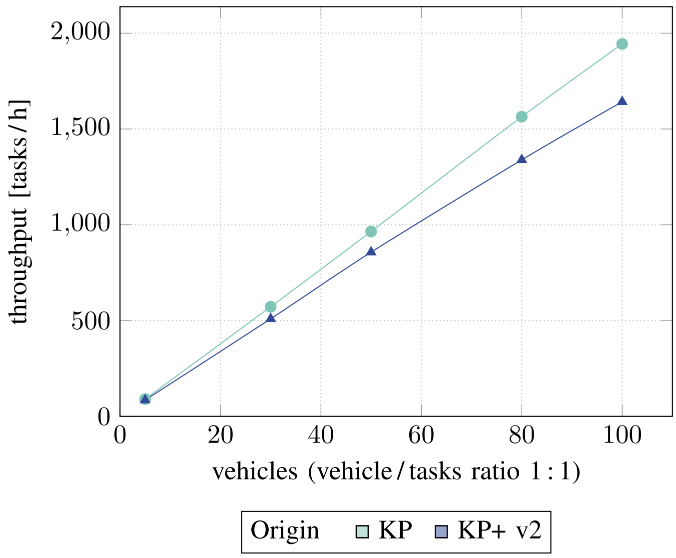

Fig. 7. Throughput measured in Tasks per Hour for KP and KP+ v2 (5,000 Samples)

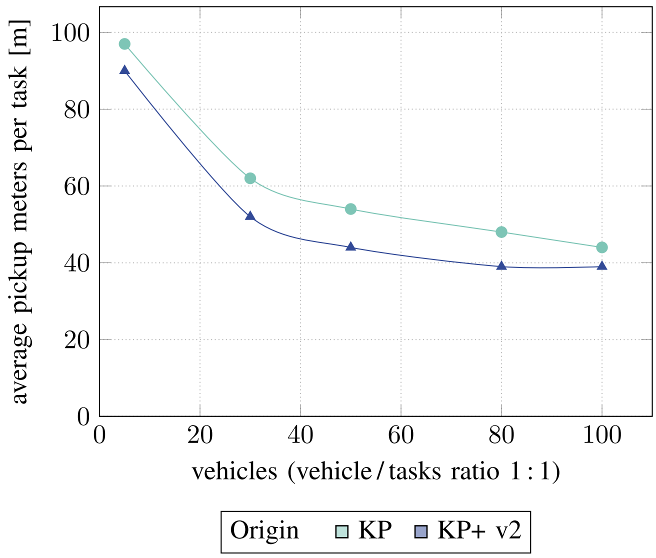

Fig. 8. Average Number of driven Pickup Meters per Task for a Vehicle / Task Ratio of 1 : 1 (5,000 Samples)

study supports the notion that using Karis Pro+ instead of Karis Pro leads to less empty drives and subsequently to a higher efficiency of the vehicle fleet. Consequently, it is suggested that a larger capacity buffer, resulting from this higher efficiency, may lead to higher flexibility for task peaks. This is turn may prevent traffic issues in large scale applications as the same goals may be achieved with lower traffic density, in comparison to the original allocation method of Karis Pro. Accordingly, the communication effort to reach this outcome is much higher than for the original method. Nevertheless, the developed simulation study demonstrated that Karis Pro+ in its final version can be considered to be a scalable method.

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