Evaluation and Control of a Collaborative Automated Picking System

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Abstract Picking is a core process of logistics. The challenge of acquiring personnel for operations and handling steadily changing product ranges can be tackled by part-wise automated picking systems to create a cooperative working environment for human pickers and picking robots. This chapter is motivated to enable a stepwise transformation from manual picking to highly automated picking processes by cooperative and learning robots. The main goal is to guarantee reliable order fulfilment by implementation of a feedback-loop between humans and robots for error handling and to gather data for machine learning algorithms to increase the performance of object detection. In this chapter a concept for measurement and evaluation of system performance is introduced ensuring successful processing of picking orders and training of picking robots to improve their ability for object detection. It is based on the amount of picking orders, the picking capacity of humans and robots, and the probability for successful automated order picking considering the training effort during system design. The proposed concept can be used for overall capacity planning as well as for operational control of picking processes.

1 Introduction

Modern supply chains are challenged by an increasing complexity and short product life cycles. Therefore, picking as central logistic process during order fulfilment must adapt to changing product ranges. Another rising challenge is the lack of personnel for manual picking processes. Therefore, automated picking systems handling steadily a changing product range become more and more important. In recent years, using technical progresses in robotics general concepts for automated picking are developed (Zou et al. 2019; Krug et al. 2016) or applied for specific use cases (Mester and Wahl

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2019). Thereby, the general concepts focus on automation of movement or manipulation of objects and not on an integrated handling of heterogenous and dynamic article ranges. Verbeet et al. (2019) propose a cooperative picking system to guarantee reliable automated picking by robots realized by a feedback-loop improving robots' ability for object detection by human support.

Classic methods for capacity planning and performance evaluation to control and design must be extended for partwise automated systems. The adaptive process model proposed by Verbeet et al. (2019) for a proposed cooperative picking system considers humans to support robots in addition to their normal workload to enable the learning process. In this system, not successful object detection during picking is the start of a learning process and therefore desired if overall order fulfilment is still guaranteed. The system is to be designed in such a way that all picking orders are completed, and the capacity of humans and robots is utilized. Furthermore, picking robots should reach their performance limits to trigger the proposed cooperative learning process to increase the picking performance of the whole system in the long term.

This chapter introduces a concept to calculate such an equilibrium of capacity for a partial automated picking system based on the adaptive process model. The calculation can be used to carry out a general capacity assessment based on available capacities and a pool of picking orders while allocating these picking orders to human pickers and robots by mathematical optimization. The overall system efficiency of picking robots' ability for object detection can be evaluated by an average probability for a successful object detection. For this, the threshold $\bar{P}_{Break}$ is calculated defining an average value for successful object detection of a single article.

The remainder of this chapter is organized as follows. In the second chapter, related work from the fields of existing robotic picking systems as well as planning and evaluation of order picking systems is discussed. This review shows the lack of a concept considering capacity during evaluation and design of cooperative partwise automated picking systems. The adaptive process model for an automated cooperative picking system is described in the third chapter. The fourth chapter proposes evaluation concepts for overall capacity planning, a preselection for order assignment and a calculation approach of a capacity-based working point. These concepts are discussed in fifth chapter and in the final chapter this paper is closed by a conclusion containing a brief summary and further research.

2 Related Work

Grosse et al. (2017) mention the following planning problems for picking systems: layout design (structure and dimension of shelfs), storage assignment (allocation of items to storage positions), zoning (assignment of working area to pickers), order batching (consolidation or splitting of picking orders), routing (sequence of picking positions and routing), and technical equipment (supporting equipment). In this paper, the problem of order assignment is added.

Many research activities focus on batching, sequencing and routing in order picking systems with multiple pickers (Scholz et al. 2017) and Chabot (2018) shows order picking is influenced most by facility layout, storage assignment policy and routing strategy. Jane and Laih (2005) improve utilization and completion time of a synchronized zone manual order picking system by a heuristic solving a natural cluster model. Yu and de Koster (2009) define order batching and zoning of the picking area using a queuing network approximation model. Bukchin et al. (2012) batch orders in a dynamic finite-horizon environment to minimize order tardiness and overtime costs of pickers using a Markov decision process-based approach to set an optimal decision-making policy. Lin et al. (2016) use Particle Swarm Optimization to solve the problems of order batching and picker routing. Zhang et al. (2017) present an approach to solve the on-line order batching and sequencing problem with multiple (manual) pickers using a hybrid rule-based algorithm minimizing turnover time (completion time of an order). In addition, they present a review about previous work about order batching. Pinto and Nagano (2020) solve the Optimized Billing Sequencing (order fulfilment) and Optimized Picking Sequence (batching, route planning) problems by combination of two genetic algorithms. Valle and Beasley (2019) discuss approaches using queueing theory, simulation, mathematical optimization and heuristics for system analysis, design optimization, and operations planning and control.

Henn (2015) is considering order assignment. The task of order assignment is strongly connected to workload balancing. In fast picking environments demand cannot be taken as known resulting in the requirement of shorter execution times of picking orders and a dynamic workload balancing (de Koster et al. 2007). Vanheusden et al. (2017) show a necessity to balance workload within a picking system not only in long-term range but also within a day or during a shift due to the steady rising requirement of flexibility. A reliable forecast is necessary to balance workload. van Gils et al. (2017) provide an overview of various time series forecasting models for predicting the workload within a picking system and indicators for measurement of accuracy of forecasting results. In van Gils (2019) different planning problems considering various real-life features to match demand and resource allocation are combined. Tu et al. (2019) focus on workload balancing within an order picking system by storage assignment. Merschformann et al. (2018) show that order assignment has the major impact on throughput of a picking system using a robotic transport system. Chen et al. (2017) combine different strategies of order sequencing, order release and storage assignment to balance workload and capacity.

Molnár (2004) suggests an integrated concept for planning a picking system by a genetic algorithm solving a constraint programming model followed by a simulation to estimate the number of pickers and picking schedule considering time constraints while minimizing total costs. Hwang and Cho (2006) plan a warehouse by minimizing costs considering throughput and storage space with a concept to measure travel time of transporters for manual picking and using a simulation model to define the necessary number of transporters. Seyedrezaei et al. (2012) present a dynamic mathematical model for the order picking planning problem maximizing order fulfilment considering product life, customer importance, probabilistic demand, and back-order strategy. Kłodawski and Jachimowski (2013) propose a concept for using an ant algorithm for planning a picking system considering various parameters but doesn't provide a definition for an evaluation function.

A mechanism to evaluate a picking system is the basis for planning and operational decisions. A qualitative approach for evaluation of a picking system is a Balanced Scorecard (Heine and Wenzel 2013). In contrast, VDI describes more than 350 KPIs for a quantitative evaluation of logistics processes (VDI 2007). Many quantitative concepts evaluate a picking system's performance by order fulfilment. Chabot (2018) uses order lead time for evaluation. Gong et al. (2010) define a framework to evaluate different storage and order picking policies by a DEA model considering total costs and service level. Brynzér et al. (1994) present an evaluation methodology using zero-based analysing of manual picking processes. Dallari et al. (2009) describe a design methodology for picking systems measuring performance by response time, picking rate and number of pickers. Pan and Wu (2012) evaluate the efficiency of a multi-picker system by estimation of the number of picking items per time to avoid inaccuracies during measurement of travel distance or travel time due to congestion. Yu and de Koster (2009) use mean throughput time of an arbitrary order as measurement of efficiency. Lamballais et al. (2017) evaluate the performance of a Robotic Mobile Fulfilment System (RMFS) that realizes a parts-to-picker environment by measuring maximum order throughput, robot utilization, and order cycle time. Hwang and Cho (2006) evaluate a system by transportation time of transporters for manual picking.

The mathematical concepts mentioned so far mainly minimize used time and travelled distance. Grosse et al. (2017) point out time to be still the most important indicator to evaluate the outcome of an order picking system. A review presented by Gu et al. (2010) shows amongst others the evaluation of performance by analytic models considering travel time or service time. Jane and Laih (2005) measure the improvement of completion time, Bukchin et al. (2012) use a measurement by slack, i.e. comparison of an order's picking time and its remaining time to supply. Zou et al. (2019) minimize the total time needed to pick items of an order. Manzini et al. (2007) evaluate performance of order picking by travel distance. Hsieh and Huang (2011) show how strategies of storage assignment, order batching and picker routing affect the overall performance also measured by travel distance Lin et al. (2016). measure the total picker routing distance. In Hernandez et al. (2017) the evaluated metrics are travel distance and travel time and Pinto and Nagano (2020) also combine these metrics by maximizing order portfolio billing and minimizing total picking time and travel distance. In Seyedrezaei et al. (2012) the degree of order fulfilment is maximized.

Hanson et al. (2018) and Jaghbeer (2019) mention the categories throughput, order lead time, availability, flexibility, quality, training time, resource utilization, costs, and ergonomics to evaluate performance of robotic picking systems. Jaghbeer (2019) states no studies using these categories for robot-to-parts picking systems exist. Even considering further technical and conceptual progress in automated picking, robots will depend on humans in order picking systems. Therefore, an efficient setup of an operational human–robot picking system needs a reliable human–machine-interaction (Azadeh et al. 2017). Bonini et al. (2019) propose a method to distribute various tasks among humans and robots within a warehouse to use synergies in human–machine-interaction. Hoffman (2019) describes the successful coordination of humans and robots as robot collaborative fluency measured by specific metrics for idle time for humans and robots each, concurrent activity, functional delay, and interaction between objectives. Within RMFS a lot of research about cooperation of transport robots delivering shelfs with articles to pickers located at static picking stations exists (Zou et al. 2019; Valle & Beasley 2019; Hanson et al. 2018). Implications for humans within a cooperative human–robot picking environment are discussed by Lee et al. (2017). An overview of different types of co-working (cell, coexistence, synchronized, cooperation, collaboration) can be found at Bender et al. (2016). RMFS can be implemented with approaches for navigation in a warehouse. Some research on navigation can be found in Nguyen et al. (2016) or Hernandez et al. (2017). Magazino realizes a picking robot capable of travelling to shelves, picking specific articles (shoe boxes) and delivering them to a transfer station (Mester and Wahl 2019). Within this system robots and humans work in parallel within a joint area. Bormann et al. (2019) show a buckling arm robot mounted on a mobile platform detecting objects by a camera system. They state the need for an adequate amount of training samples to enable a reliable object detection. The collection of these samples is automated by an object recording station collecting colored 3d point clouds. Furthermore, different systems for bin picking (Martinez et al. 2015) or shelf picking (Liang et al. 2015; Zhang et al. 2016; Zhu et al. 2016; Wahrmann et al. 2019) are proposed. Gripping of complex formed articles is discussed by Liu et al. (2019) and Kozai and Hashimoto (2018) calculate the risk for collision in case of different objects in a picking scene. Verbeet et al. (2019) describe a cooperative human–robot picking system using an integrated feedback-loop to improve the ability of object detection of robots. The following section explains this concept in detail.

3 Cooperative Picking System

Rieder and Verbeet (2019) present an adaptive process model to realize a cooperative picking system containing an Application-Phase and a Learning-Phase. This model was extended by Verbeet et al. (2019) by an Adjustment-Phase and a Cooperation-Phase as well as by a conceptual picking system describing its components and their interactions. The model is shown in Fig. 1. Within the Learning-Phase models for object detection are created and improved using image data recorded in a controlled environment as well as data from operational processes. This phase is decoupled from operational order picking within the Application-Phase where humans and robots work in parallel within a picking environment. A picking robot is supposed to successfully grip and withdraw from a storage location after a successful object detection. In case of an unsuccessful object detection it tries to find a solution on its

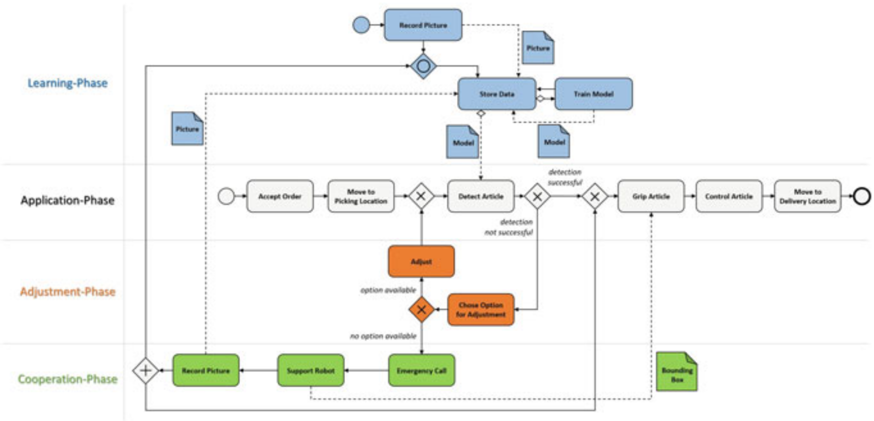

Fig. 1 Adaptive process model for picking-robots (Verbeet et al. 2019)

own by predefined options during the Adjustment-Phase, e.g. by moving its camera to a different position. If this is not successful, the Cooperation-Phase is triggered calling a human picker (Emergency Call) to support the robot by picking the article and generating feedback for an improvement of object detection. This feedback contains image data gathered from the operative situation at the shelf by the robot's camera and information added by the human picker (article-ID, position of article defined by a bounding box) to enable training.

The process model can be realized using an agent-based system architecture, whose components are shown in Fig. 2. A Warehouse-Managemen-System (WMS) is responsible for administration of inventory data and allocation of picking orders. Human pickers and picking robots cooperatively process assigned orders, whereby human pickers are interacting with IT systems and picking robots by wearables (Kong et al. 2019). Furthermore, a Picture Recording Machine is used for efficient and controlled image recording (Rieder and Verbeet 2019). These images are stored on a data server and are used for training of models for object detection by a computation cluster. Communication is realized by MQTT enabling topic controlled publishing and receiving of FIPA-conform Agent Communication Language (ACL) messages. Interaction patterns define the sequence of messages between components and embed it into the picking processes.

Each article can be successfully detected by a picking robot with a probability of P_{OD}. An average probability is introduced to evaluate picking robots' performance for successful object detection. The working points P_{Break} ($Effort_{Robot} = Benefit_{Robot}$), P_{Human} ($Error_{Robot} = Error_{Human}$), and $P_{Improve}$ ($Epoch\text{-}\Delta = \delta_{Limit}$) are defined. This probability describes the efficiency of object detection but not the overall performance of the system. Regarding the overall system performance, the capacity of human pickers and picking robots and the effort for Emergency Calls resulting from unsuccessful object detection must be considered. The assignment of orders to human pickers and picking robots during the interaction pattern "Picking Order" is of major

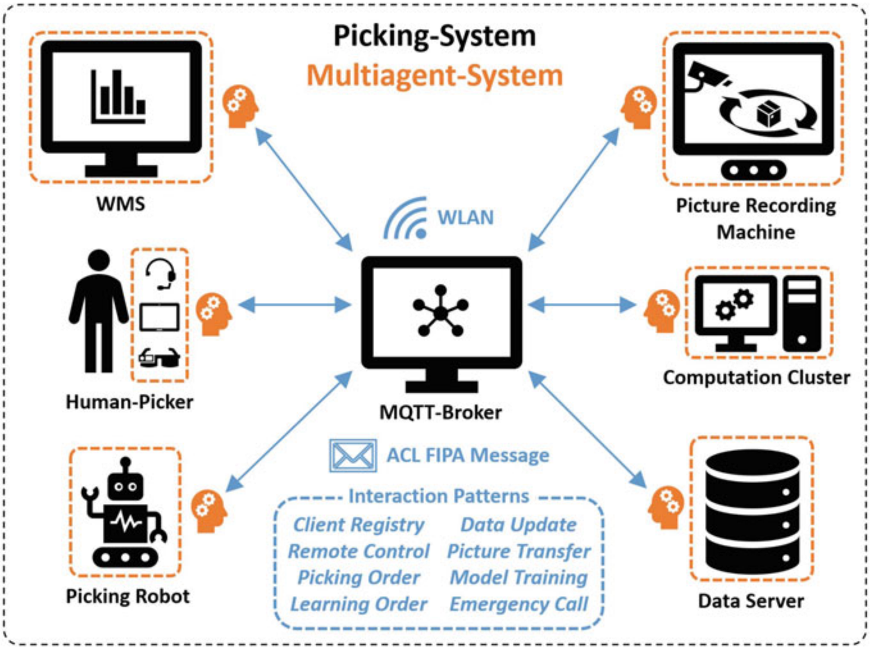

Fig. 2 Picking system to realize the adaptive process model according to Verbeet et al. (2019)

importance within this capacitive evaluation because it enables workload balancing. It is realized by a one-stage auction process arranged according to Contract Net Protocol (FIPA 2001) allocation orders depending on the effort for order fulfilment measured by time and using current workload, order lead time and duration of probably arising Emergency Calls.

The adaptive process model must reserve capacity to allow the feedback-loop to improve object detection. Therefore, an equilibrium between order fulfilment and improvement must be found, i.e. a working point must be defined at which fulfilment of all picking orders is guaranteed but robots are free to cause Emergency Calls to gather operational data. In the following chapter, a calculation for such an equilibrium is presented to setup picking capacity and control order assignment ensuring order fulfilment while maximizing robots' workload to trigger Emergency Calls.

4 System Evaluation

The general approach is a capacitive evaluation of the performance of a picking system. It can be used for proactive capacity planning or operational control of order assignment. Moreover, an approach for an overall performance evaluation of picking robots' ability for object detection is proposed according to the classification of

Verbeet et al. (2019) using a minimal probability of object detection $_{\text{Break}}$ to define an efficient working point for picking robots.

4.1 Capacity Planning of Picking System

According to the adaptive process model picking orders can be fulfilled by humans and robots in parallel. The overall picking performance of a system is reduced by the robots' dynamic learning process respectively by Emergency Calls. The following calculation enables the evaluation if a specific order assignment, i.e. an allocation of picking orders to human pickers and picking robots, allows the execution of all orders with the existing capacity. Basis for this calculation is a demand forecast for a time interval, e.g. one shift, containing articles and their number of picks, whereby this forecast is divided into two subsets for humans and robots each:

$$\mathrm{D_F} = \sum_{\text{Article, Forecast}} \mathrm{Picks}_{\text{Article, Forecast}} \tag{1}$$

$$\begin{aligned} \mathrm{D_F} &= \mathrm{Subset}_{\text{Robot}} + \mathrm{Subset}_{\text{Human}} \\ &= \sum_{\text{Article, Robot}} \mathrm{Picks}_{\text{Article, Robot}} + \sum_{\text{Article, Human}} \mathrm{Picks}_{\text{Article, Human}} \end{aligned} \tag{2}$$

During the processing of orders from $\mathrm{Subset}_{\text{Robot}}$, unsuccessful object detection can trigger an Emergency Call leading to a time effort for human ($\mathrm{L}_{\text{EC,H}}$) and robot ($\mathrm{L}_{\text{EC,R}}$). This effort is assumed to be constant for a picking system and can be evaluated from empirical data (Verbeet et al. 2019). The expected total effort for human pickers and picking robot is the sum of the effort for a single Emergency Call multiplied with the probability for an unsuccessful object detection weighted by the number of picks from $\mathrm{Subset}_{\text{Robot}}$:

$$\mathrm{L}_{\text{EC,H,SR}} = \sum_{\text{Article, Robot}} \left(\mathrm{Picks}_{\text{Article, Robot}} \cdot \mathrm{L}_{\text{EC,H}} \cdot \left(1 - \mathrm{P}_{\text{OD, Article}}\right)\right) \tag{3}$$

$$\mathrm{L}_{\text{EC,R,SR}} = \sum_{\text{Article, Robot}} \left(\mathrm{Picks}_{\text{Article,Robot}} \cdot \mathrm{L}_{\text{EC,R}} \cdot \left(1 - \mathrm{P}_{\text{OD, Article}}\right)\right) \tag{4}$$

A picking capacity for human pickers ($\mathrm{C_H}$) and picking robots ($\mathrm{C_R}$) is calculated by multiplying an individual picking rate (picks per time unit) depending on warehouse organisation and picking environment with the number of humans respectively robots:

$$C_H = \text{PickingRate}_{\text{SingleHuman}} \cdot \text{Number}_{\text{Human}} \tag{5}$$

$$C_R = \text{PickingRate}_{\text{SingleRobot}} \cdot \text{Number}_{\text{Robot}} \tag{6}$$

In addition, an effective working time (WT) without breaks, charging or technical down time within the time interval of the forecast is defined. The two subsets must be defined in such a way that they can be fulfilled with the existing picking capacity:

$$C_H \cdot WT - \frac{L_{EC,H,SR}}{WT} \geq \text{Subset}_{\text{Human}} \tag{7}$$

$$C_R \cdot WT - \frac{L_{EC,R,SR}}{WT} \geq \text{Subset}_{\text{Robot}} \tag{8}$$

To enable a picking system to fulfil all picking orders the effective picking capacity of all humans and robots reduced by the capacity to handle Emergency Calls must be greater than or equal to the demand forecast. Therefore, the following equilibrium is defined:

$$C_H \cdot WT - \frac{L_{EC,H,SR}}{WT} + C_R \cdot WT - \frac{L_{EC,R,SR}}{WT} \geq D_F \tag{9}$$

The linear optimization model from Fig. 3 is based on the Eqs. (1)–(9) and calculates the subsets. The goal is to maximize the workload of robots and humans subject

```
execute { cplex.epgap = 0.0001; }

//********************** Variables *********************************************
int WT = ...;         float C_H = ...;           int numArticle = ...;
int L_EC_H = ...;     float C_R = ...;           range Articles = 1..numArticle;
int L_EC_R = ...;     int D_F[Articles] = ...;   float POD[Articles] = ...;

//********************** Decision Variables **********************************
dvar int SubsetRobot;   dvar float L_EC_H_SR;   dvar int+ PicksRobot[Articles];
dvar int SubsetHuman;   dvar float L_EC_R_SR;   dvar int+ PicksHuman[Articles];

//********************** Goal Function ****************************************
maximize SubsetRobot;

//********************** Constraints *****************************************
subject to {
    SubsetRobot == sum(i in Articles)(PicksRobot[i]);
    SubsetHuman == sum(i in Articles)(PicksHuman[i]);
    forall(i in Articles) D_F[i] == PicksRobot[i] + PicksHuman[i];
    L_EC_H_SR == sum(i in Articles)(PicksRobot[i] * L_EC_H * (1 - POD[i]));
    L_EC_R_SR == sum(i in Articles)(PicksRobot[i] * L_EC_R * (1 - POD[i]));
    SubsetRobot <= (C_R * WT) - (L_EC_R_SR / WT);
    SubsetHuman <= (C_H * WT) - (L_EC_H_SR / WT);
};
```

Fig. 3 Calculation of subsets by linear programming in OPL to capacity restrictions and total order fulfilment. Therefore, robots are assigned as many picking orders as possible to learn from resulting Emergency Calls. The model is programmed in OPL using OPL-Studio 12.8.0.0 (IBM 2020).

The picking system is modelled by the constant input parameters working time WT, theoretical picking capacity (C_R and C_H) and a set of articles each possessing a probability for successful object detection P_{OD}. Constraints are the capacity restrictions from Eqs. (7) to (8). The subsets are defined by the additional variables PicksRobot and PicksHuman defining the number of picks of an article within its corresponding subset. After introducing these variables, order fulfilment can also be defined as constraint by matching the sum of PicksRobot and PicksHuman against an article's picks within D_F.

4.2 *Preselection for Order Assignment*

The equilibrium defined by Eq. (5) can also be used for a preselection during order assignment. Two variants are introduced: the generation of a list of articles which may be assigned to a robot and the calculation of a threshold $\bar{P}_{OD}$ for the expected probability for successful object detection during order picking.

4.2.1 Preselection by Article List

If the articles of a picking order are part of $Subset_{Robot}$, robots are considered by the WMS during order assignment process. There is no need for a robot-specific assignment: Offering many human-only orders will stepwise increase their workload (order queue). When orders accessible by robots are offered, this workload will increase their effort values increasing the probability robots will win the auction. The effect of this mechanism is shown in Fig. 4.

It assumes the initial forecast D_F in total is reliable within working time WT but does not consider the variation of $Demand_{Real}$ over time. Therefore, it must be encountered by a feedback control during operation. At first, an initial calculation of subsets is using a linear smoothed total demand D_F for WT as $Demand_{Calculation,0}$. By a rolling recalculation which is based on the remaining working time and the difference of executed orders and original forecast new subsets are defined. In each recalculation a new P_{OD} for an article can also be considered. These recalculations are heavily affected by the rolling time span: the smaller the time span, the more effective is the matching of forecast and real demand. In contrary, the system is not allowed to trigger many Emergency Calls and learning is limited. Greater time spans allow higher delay during order fulfilment but enable a higher amount of Emergency Calls and thereby more input data for learning.

In Fig. 4 recalculations for the time values t_1, t_2 und t_3 are shown. Even if all existing orders are fulfilled at t_1, the number of executed orders C_1 is beneath the

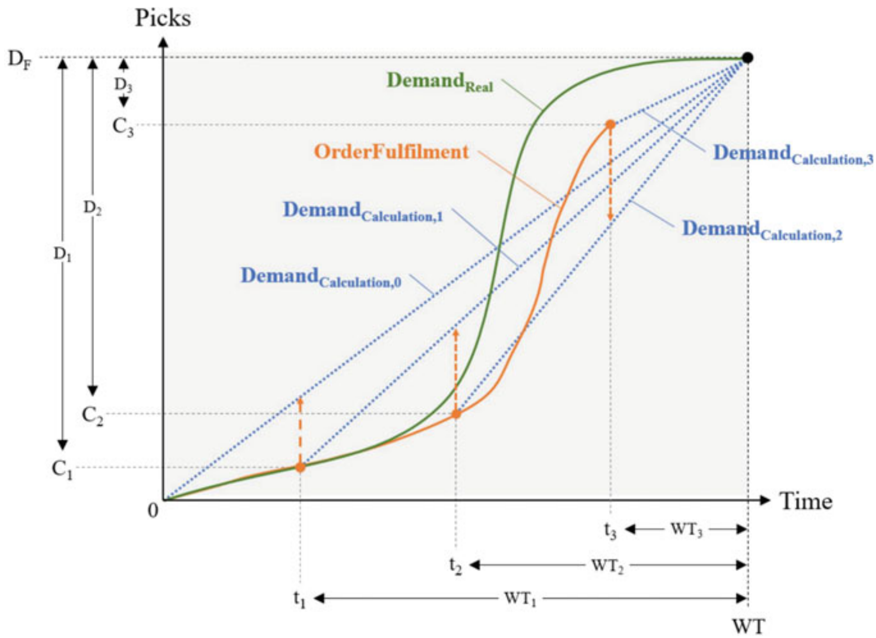

Fig. 4 Concept for a rolling calculation of subsets for a preselection before order assignment

calculated $Demand_{Calculation,0}$ resulting in lower capacity for Emergency Calls and "pulling" OrderFulfilment upwards. The same effect can be observed at t_2, whereby actually a real backlog of picking orders exists. At t_3, the number of executed orders is above the last recalculation $Demand_{Calculation,2}$ and more capacity for Emergency Calls is considered during the calculation of subsets, although the backlog still exists.

The question arises why a preselection is necessary during an order assignment by an auction which inherently should balance the workload. One reason is the variation of demand during WT. If an order's deadline for fulfilment is the end of WT, a statistical approach is sufficient because temporary backlog induced by Emergency Calls can be caught up over time. But if too much capacity is bound by Emergency Calls and due times for picking orders exist, there must be a regulating mechanism. Free capacity at the end of WT resulting from this mechanism can be used for learning orders described in Verbeet et al. (2019) to further improve object detection. A problem according to this mechanism can arise from the calculation of subsets by the linear program. Its solution is not unique, and articles can occur rarely in a subset. This effect could be avoided by further constraints or some higher meta control of the optimizing.

4.2.2 Preselection by Threshold

The forecast D_F is defined as a set of picks, i.e. no connection between picks and articles exists and the subsets are abstract volumes of picks. A threshold $\bar{P}_{Threshold}$ is calculated according to the expected probability of object detection for the articles of $Subset_{Robot}$ and is compared with $\bar{P}_{Order}$ before the initial call for bids during order assignment. However, the P_{OD} of a single article can be lower than $\bar{P}_{Threshold}$. In general, $\bar{P}$ is defined as the arithmetic mean of object detection P_{OD} weighted with the set of picks for a set of articles as shown in Eq. (10). Thereby, Eqs. (3) and (4) can be defined by using a constant value for object detection:

$$\bar{P} = \sum_{Article}\left(\frac{Picks_{Article}}{\sum_{Article} Picks_{Article}} \cdot P_{OD,\,Article}\right) \tag{10}$$

$$L_{EC,H,SR} = Subset_{Robot} \cdot L_{EC,H} \cdot \left(1 - \bar{P}_{Subset,\,Robot}\right) \tag{11}$$

$$L_{EC,R,SR} = Subset_{Robot} \cdot L_{EC,R} \cdot \left(1 - \bar{P}_{Subset,\,Robot}\right) \tag{12}$$

The linear program shown in Fig. 3 is modified by defining a subset as a set of picks. Using the Eqs. (11) and (12) the article-specific P_{OD} is replaced by a constant value. This value is minimized by the goal function. The equilibrium from Eq. (5) is still a constraint forcing the calculated P_{OD} to be the smallest value allowing an allocation of subsets. However, the goal function loses its linearity by this modification and therefore the optimization model is solved by Constraint Programming (using CP) in OPL-Studio. This also makes a modification by "dexpr" and a scaling-factor of 100 necessary because this method only accepts integers. The resulting optimization model is shown in Fig. 5.

At recalculation the set of executed picks and the remaining working time are updated. If there are more executed orders than expected, more capacity for Emergency Calls is released, $\bar{P}_{Threshold}$ is reduced, and robots are assigned more picking orders. In contrast, if execution is beneath the expected value, P: $^{-}_{Threshold}$ must be increased to raise picking performance by reducing the chance of triggering Emergency Calls. This approach is using a general P_{OD} enabling the handling of articles with a weak P_{OD} by picking robots. On the other hand, control of operational order fulfilment is weaker as picks are treated independent from articles.

```
using CP;

//*********************** Variables *******************************************
int WT = ...;          float C_H = ...;             int numArticle = ...;
int L_EC_H = ...;      float C_R = ...;             range Articles = 1..numArticle;
int L_EC_R = ...;      int D_F[Articles] = ...;

//*********************** Decision Variables **********************************
dvar int+ SubsetRobot;             dvar int+ SubsetHuman;
dvar int+ scalePOD;                dexpr float POD = scalePOD/100;
dvar int scaleL_EC_H_SR;           dexpr float L_EC_H_SR = scaleL_EC_H_SR/100;
dvar int scaleL_EC_R_SR;           dexpr float L_EC_R_SR = scaleL_EC_R_SR/100;

//*********************** Goal Function ***************************************
minimize POD;

//*********************** Constraints *****************************************
subject to {
    sum(i in Articles)(D_F[i]) == SubsetRobot + SubsetHuman;
    L_EC_H_SR == SubsetRobot * L_EC_H * (100 - POD);
    L_EC_R_SR == SubsetRobot * L_EC_R * (100 - POD);
    SubsetRobot <= (C_R * WT) - (L_EC_R_SR / WT);
    SubsetHuman <= (C_H * WT) - (L_EC_H_SR / WT);
};
```

Fig. 5 Calculation of $\bar{P}_{Threshold}$ by linear programming in OPL

4.3 Definition of Working Point for System Efficiency

Verbeet et al. (2019) introduce different thresholds to evaluate object detection of an article. P_{Break} is of major importance for real applications defining an equilibrium of effort for Emergency Calls and successful picks by robots. But to evaluate the efficiency of robots the overall system performance must be considered. A system can work in an efficient way even if the probabilities of object detection for single articles are less than P_{Break}. Consequently, an average probability of object detection for all articles is defined as well as an equilibrium between effort and benefit of using robots.

The Eqs. (13) and (14) calculate an expected effort for humans ($L_{EC,H,F}$) and robots ($L_{EC,R,F}$) for the forecast D_F. In Eq. (15) an equilibrium is defined equalizing the picking capacity of robots reduced by their effort due to Emergency Calls, i.e. their effective picking capacity and the effort of human pickers for handling Emergency Calls:

$$L_{EC,H,F} = D_F \cdot L_{EC,H} \cdot \left(1 - \bar{P}\right) \tag{13}$$

$$L_{EC,R,F} = D_F \cdot L_{EC,R} \cdot \left(1 - \bar{P}\right) \tag{14}$$

$$\frac{L_{EC,H,F}}{WT} = C_R \cdot WT - \frac{L_{EC,R,F}}{WT} \tag{15}$$

Therefore, by P; − the capacity human pickers must reserve for error handling is defined. However, this does not give any information about the ability of the picking system to fulfil all picking orders. This is guaranteed by meeting Eq. (9). In this case $\bar{P}$ matches $\bar{P}_{Break}$ and can be calculated by transforming Eq. (15):

$$\bar{P}_{Break} = 1 - \frac{C_R \cdot WT^2}{D_F \cdot (L_{EC,R} + L_{EC,H})} \quad (16)$$

Comparing $\bar{P}_{Break}$ and $\bar{P}_{Real}$ the efficiency of picking robots can be evaluated, whereby $\bar{P}_{Real}$ is calculated from real probabilities for object detection P_{OD}:

$\bar{P}_{Break} > \bar{P}_{Real}$: Human pickers must expend more capacity for handling Emergency Calls than robots can compensate by executing successful picks, i.e. the effective picking capacity of the system would be higher without robots.

$\bar{P}_{Break} = \bar{P}_{Real}$: The effort of human pickers for handling Emergency Calls and contribution of successful picks executed by robots equals each other. At this point, the system benefits from the collection of data to improve the ability of object detection of the picking robots resulting in an increasing $\bar{P}_{Real}$.

$\bar{P}_{Break} < \bar{P}_{Real}$: Picking robots are working efficient, meaning the effort of humans and robots for handling Emergency Calls is smaller than robots' contribution by executed picks. Consequently, the effective picking capacity is increased by the deployment of robots.

5 Discussion

The presented calculation approaches specify the mechanism for order assignment of the interaction pattern "Picking Order" and enable a capacitive evaluation of the picking system. However, the static input variables are problematic, i.e. the time requirements for calculating the effort value during order assignment and the empirical loss values for an Emergency Call $L_{EC,H}$ and $L_{EC,R}$. These assumptions make sense for a sufficiently large picking system that is evaluated over a longer period, so the real expectancy values match with the values of the assumptions. In systems with strongly fluctuating travel times, assuming constant effort can lead to an unacceptable weighting of P_{OD}. Therefore, the mentioned input variables should be calculated dynamically. For the calculation of the duration of an emergency call, standardized time assessments of processes such as MTM (Britzke 2010) can be used to calculate them context-dependent. Empirical data can be generated from an operative system using the approach described by Feldhorst (2018). Within robots, time values can be derived from calculations of their internal controller.

The preselection based on the capacitive equilibrium from Eq. (5) requires a static forecast for a time interval. This assumption is acceptable in systems with plannable or predictable demands. Without such a known lead a system can only be controlled reactively making the concept not reliable, because fluctuating demand must be covered by additional time buffer or resources. Alternatively, a forecast could be generated for each recalculation based on current order data and empirical values from previous periods. The threshold calculation is a statistical approach allowing a system to fluctuate to a certain degree and only slightly limits the auctioning process of order assignment. However, an empirical study must show whether the calculated threshold values are reliable. The approach tends to be more resilient the more complex the system is, i.e. the more articles exist, and the more robots and humans can process orders. The calculation of P_{Break} is an approach to evaluate the general efficiency of picking robots. In Verbeet et al. (2019), the additional working points P_{Human} and $P_{Improve}$ are also defined, whereby $P_{Improve}$ describes a very artificial value which can only be achieved in exceptional cases in operational systems. Most articles are expected to reach values between P_{Break} and P_{Human} to meet the capacity restrictions and ensure order processing.

The evaluations are based on a capacitive view of humans and robots and initially do not make any statements about economic aspects of the picking system. For such a consideration, an additional cost model would have to be integrated into the calculation. This cannot be formulated generally for the heterogeneous requirements and technical specifications of picking systems, which is why a capacitive approach was chosen in this paper.

6 Conclusions

The challenge of finding personnel for picking and handle continuously changing article ranges can be countered with partially automated picking systems creating a cooperative working environment for humans and picking robots. The motivation is to ensure reliable order fulfilment by implementation of a feedback-loop (Emergency Call) between humans and robots for error handling and data collection for machine learning algorithms in order to continuously improve object detection and thereby improve overall performance of picking robots. In this paper, a concept for measurement and evaluation of system performance to ensure the processing of picking orders and the training of picking robots is introduced.

The proposed approach is using a capacitive evaluation of a picking system to define equilibrium between the requirements of order processing, the picking performance of humans and robots and the effort for improving object detection of the robots. In a picking system this equilibrium can be used for strategic evaluation of the automated picking performance of robots (working point), for tactical resource planning (capacity planning) or for operational workload balancing (order assignment). Even if this evaluation mechanisms extend the adaptive process model and the conceptual picking system, there are still open questions for future research.

The presented calculation uses static assumptions for actually dynamic parameters making its equations only reliable for complex systems considering a sufficiently long runtime. However, the evaluation concept can be expanded by context-based calculations using MTM-based approaches. The actions of robots can be evaluated based on functions of their internal control, e.g. travel time between picking locations as outcome from path planning.

The components for a demonstrator, which is to validate the presented evaluation approach with empirical data, have been developed at Ulm University of Applied Sciences in recent months. The configuration of these components and the definition of suitable scenarios are still pending and will be completed soon. The evaluation approach will also be integrated into an intra-logistic scenario with real robots. These provide context-dependent estimations for the required time of their actions in order to enable a dynamic and context-based calculation of time effort and fulfilment time during order processing.

The model for object detection is also subject of current research. In current work, a singular neural network is used for the detection of all existing articles in a picking system. An alternative approach pursues the dynamic combination of several neural networks for one article each, which are compared for object detection with one another by an algorithm based on their storage locations provided by an overall WMS. This is intended to modularize object detection and shorten training times. The comparison "singular" versus "combined" can also be carried out by the demonstrator.

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