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Concept of Highly Flexible Material Flows Based on Unmanned Aerial Vehicles in a Smart Factory Grid

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Abstract

The increasing variety of product variants, short product life cycles and volatile operating conditions require highly flexible and adaptive production and intralogistics systems. Particularly in matrix production systems, production and material flow decisions must be tightly coupled and dynamically coordinated in order to ensure efficiency, robustness and adherence to delivery dates. This paper presents a concept for highly flexible material flows in a Smart Factory Grid (SFG), addressing the use of Unmanned Aerial Vehicles (UAVs) as a central intralogistics element. The proposed concept is based on a three-stage hierarchical architecture consisting of the subsystems *Dynamic Production Scheduling*, *Route Allocation* and *Trajectory Planning*. Incoming production orders comprising different operations are submitted to the *Dynamic Production Scheduling* for adaptive assignment of manufacturing resources and transport tasks, considering time, cost, and energy objectives as well as logistical constraints. The *Route Allocation* provides centralized, deterministic coordination of the UAVs in shared airspace through a layered level structure that enables collision-free, predictable and reproducible flight routes. Building on this, the *Trajectory Planning* computes energy- and time-efficient trajectories and augments them with reactive online planning to safely handle dynamic obstacles. The combination of these subsystems enables a robust coupling of production and material flow planning in highly dynamic environments and addresses key challenges such as scalability, safety, plan stability and resilience.

Keywords

Smart Factory Grid (SFG), Material Flow, Unmanned Aerial Vehicle (UAV), Dynamic Production Scheduling, Route Allocation, Trajectory Planning

1 Introduction

In recent years, the variety of product variants has continuously increased, forcing companies to meet increasingly individualized customer requirements. Particularly in high-wage countries, shortened product life cycles and small batch sizes pose major economic challenges. To remain competitive, production processes must therefore be designed to be more flexible and efficient [1].

With this background, research on matrix production systems [2, 3] and freely linked assembly systems [4] have gained importance, as these approaches dissolve the rigid coupling between production facilities and material flow systems. Within the framework of the Forschungsimpuls funded by the German Research Foundation (DFG) titled *“Smart Factory Grids: Methodiken für eine servicebasierte, hochflexible, dynamisch verteilte Fertigung mit autonomen, adaptiven und resilienten Systemen”*, the Esslingen University of Applied Sciences is actively involved with several research groups [5].[2] The

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Virtual Automation Lab (VAL) focuses on the adaptive control of flexible material flows and machine assignment in the SFG. Central research questions include the optimal utilization of available production resources as well as the realization of the resulting material flows between processing stations. In addition to ground-based intralogistics systems, the use of autonomous indoor UAVs is investigated in particular, as their agility and flexibility can significantly increase the dynamics of material flows in the SFG [6].

This paper presents a solution concept that realizes the multi-criteria optimization of manufacturing processes (e.g., cost, time, energy) as well as the control of material flows in the highly dynamic SFG through three subsystems (see Figure 1).

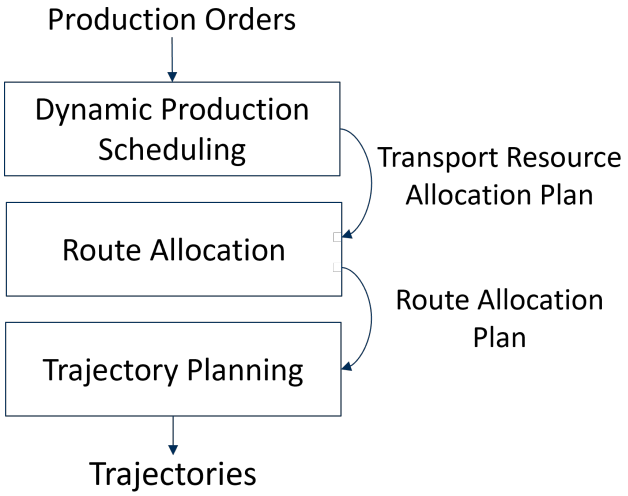

Figure 1: Concept for subdividing the material flow into subsystems

In the *Dynamic Production Scheduling* subsystem (see Chapter 3), production orders are decomposed into individual operations. Each operation must be assigned to one of several eligible machines and sequenced accordingly, while the required transport tasks are allocated to available transport resources. The resulting *Transport Resource Allocation Plan* is passed to the *Route Allocation* subsystem (see Chapter 4), which is responsible for the coordination and flight level assignment of the flying robots within the available airspace. In the final *Trajectory Planning* subsystem (see Chapter 5), safe, time- and energy-efficient flight trajectories are computed, which are ultimately executed by the UAV.

2 Definition and Concept of the Smart Factory Grids (SFGs)

Matrix production refers to a modularly structured production system in which process-segmented production resources are flexibly and non-cyclically interconnected. Orders pass exclusively through the process modules required for them, whereby both the sequence of operations and the assignment to resources can be designed variably. Characteristic features include a loose to elastic coupling of modules, the capability of lot size one production and a high adaptability to volatile operating conditions. Depending on the specific implementation, structural reconfigurations, adaptive order control, or a combination of both are realized, enabling matrix production systems to achieve high flexibility, reconfigurability and productivity. Ranke et al. provide a comprehensive categorization of different types of matrix production systems in their paper [3].

The SFG can be regarded as a specific manifestation of a cyber-physical matrix production system according to the categorization of Ranke et al. Like other cyber-physical matrix production systems, the SFG is characterized by periodic reconfiguration of operating resources and flexible order control during order execution. It thus corresponds to the most advanced form of a matrix production system and enables a high degree of flexibility, reconfigurability and productivity [3]. In addition to Ranke et al., the SFG is defined as a practically implementable realization within the context of matrix production systems. It therefore not only provides a theoretical frame of reference, but also serves as a guiding principle for the operational implementation of real systems.

Central to the understanding of SFGs is the role of Micro Manufacturing Units (MMUs), which act as autonomous atomic production modules. A MMU corresponds to a fully self-contained manufacturing module that performs exactly one (elementary) manufacturing operation, for example milling a part, applying a coating, or assembling a component. The individual MMUs are equipped with a standardized interface, which is served by an autonomous material flow system based on UAVs and Unmanned

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Ground Vehicles (UGVs).[3] By combining multiple MMUs, complex manufacturing processes can be realized that exhibit a high degree of flexibility and adaptability. Only in this way, from our perspective, the flexibility inherent in matrix systems can be made usable in real operation while simultaneously increasing the robustness of the system.

In the context of SFGs, particular emphasis is placed on the aspect of smart behavior. Such a system should not only be flexible and consist of fully interconnected subsystems, but also be able to respond proactively to unforeseen events. Failures of individual modules or machines must be compensated for, and alternative production paths must be generated automatically. The goal is a production system that operates uninterrupted 24/7, independently identifies, evaluates and resolves disturbances and thus exhibits a largely autonomous self-organization. With this claim of connectivity, resilience and autonomy, the SFG differs from conventional flexible manufacturing concepts and makes it a central building block of future industrial value creation.

3 Dynamic Production Scheduling

In the SFG, manufacturing orders are executed as sequences of multiple operations: Each operation is assigned to a suitable MMU, while the required interoperation material flow is handled by intralogistics systems. This enables a highly variant-rich product portfolio. The scheduling **task** is to determine the assignment, order and start times of these operations such that capacities and due dates are met while simultaneously minimizing throughput time and resource usage, with the required material flow supplying the MMUs in time – in this contribution mainly by UAVs. Since orders arrive continuously, resource availability changes and processing as well as flight times vary, this is not a one-time offline planning task, but a continuous decision-making problem in short cycles [7].

Trade-offs arise from multiple perspectives. On the one hand, typical production objectives such as throughput time, due-date adherence and utilization must be considered. On the other hand, transport- and UAV-specific objectives and constraints come into play, such as energy demand, state of charge, availability of takeoff/landing and handover points, as well as safety-critical requirements in the airspace (e.g., minimum separation, no-fly zones and conflict-free operation). Overall, this yields an integrated, multi-criteria, event-driven scheduling problem that must satisfy hard constraints (capacities, due dates, safety requirements) in ongoing operations with low decision latency.

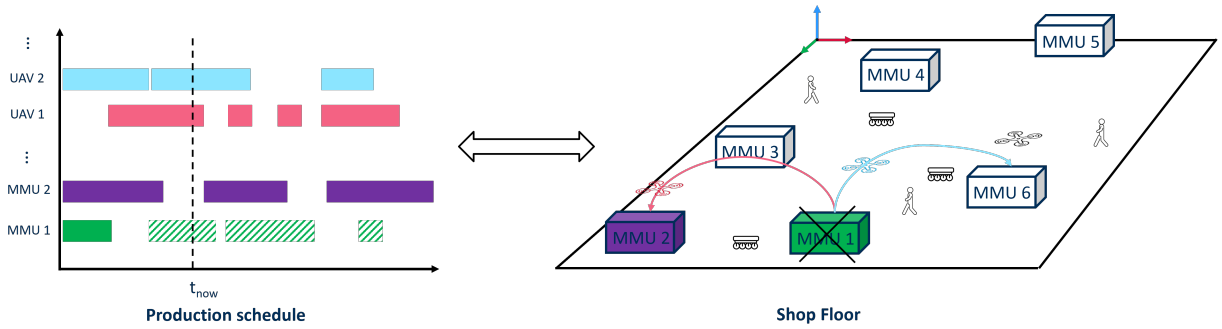

Figure 2: Reactive production plan adjustments to dynamic events (here: failure of MMU 1).

As a consequence, production-plan feasibility depends directly on feasible material flow: transport decisions shape production start times and sequences, while production assignments determine transport demand, bottlenecks and airspace conflicts. Thus, separately optimizing production and transport is only partly suitable in the SFG context and should be complemented by coupling mechanisms or integrated models. Figure 2 illustrates this via a Gantt chart of order operations on multiple MMUs, with tightly linked UAVs transport tasks ensuring on-time supply. It also highlights the need for dynamic

[3] Because product dimensions, weights and time constrains vary, operating the SFG requires both UAVs and UGVs. Nevertheless, this paper focuses exclusively on UAVs.

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reactions to failures and changes, exemplified by the failure of MMU 1 and the resulting plan adjustment.

The design of scheduling and material-flow decisions in the SFG is shaped by four key **characteristics**.

1. Scalability and heterogeneity demand short decision cycles despite many resources (e.g., MMUs, machines, buffers, handover points) and simultaneously deployed UAVs, enlarging both solution and state spaces for consistent decisions.

2. The event-driven, reconfigurable SFG makes static plans quickly obsolete due to continuous arrivals and topology changes (e.g., resources added/removed, capacity shifts, restricted zones). Hence, incremental re-planning is needed without full re-optimization after every event.

3. Disruptions and uncertainty (resource failures, variable processing/flight times, battery) must be handled to stay resilient while avoiding instability from frequent, large-scale rescheduling, suggesting robust high-level decisions with local repair.

4. Highly coupled material flow links transport and production planning: short transports, bottlenecks at takeoff/landing and handover points and conflict-free airspace use (e.g., separation, reservations, no-fly zones) constrain feasible start times and sequences. Scheduling must therefore include transport constraints to ensure executability.

For scheduling in the SFG, the **literature** distinguishes several complementary approaches that exhibit different strengths depending on problem size, degree of dynamism and required responsiveness. Especially for strongly coupled production and transport decisions, it has been shown that hybrid strategies are often used in which different methodological layers are combined. Optimization-based methods, such as Mixed Integer Programming (MIP) or Constraint Programming (CP), are primarily suitable for small to medium-sized sub-instances or limited planning horizons [8]. They are often used to ensure feasibility, model constraints explicitly and compute local improvements. For large and highly dynamic instances in the SFG, such approaches are generally only practical via decomposition, rolling-horizon planning, or as embedded sub-optimizers due to their computational effort. Metaheuristics and hybrid matheuristics are well established particularly for (flexible) job-shop variants and integrated transport couplings [9]. They make it possible to find good solutions even in large search spaces and can be extended with local search or repair steps so that they can quickly adapt to events (e.g., resource failures, new orders). In practice, they are therefore often used as a central optimization component that is updated periodically or event-driven. Online heuristics and dispatching approaches primarily target very short decision times and robust, consistent decisions during ongoing operations [10]. They are particularly suitable when event rates are high or when fast fallback decisions are needed. Typically, quality limitations of these local decisions are addressed through higher-level guiding plans, priority rules, or periodic re-optimization. Learning-based approaches, especially Deep Reinforcement Learning (DRL), are attractive because they enable state-based decisions in online operation and can potentially be evaluated very quickly [11]. However, key challenges lie in reliably satisfying hard constraints (e.g., due dates and safety restrictions) and in generalizing to changing system states and topologies, as occur in the SFG due to reconfiguration and volatile resource availability.

As a **proposed concept** for SFG scheduling, a multi-stage, hybrid planning and control architecture is promising. Purely global optimization methods often deliver high plan quality, but for large, dynamic instances they are only of limited use in short decision cycles. Conversely, purely local online decisions are highly responsive and robust to events, but without an overarching structure they can lead to suboptimal or unstable planning (e.g., due to short-sighted decisions, frequent rescheduling, or failing to meet global due-date and energy targets). A suitable architecture therefore combines a more global guiding plan with a local, event-driven online control. The *guiding plan* operates on a medium time horizon and generates consistent framework decisions for order assignment and capacity utilization. In doing so, it sets guardrails for due-date and energy targets and considers the transport side at least in aggregated form, for example via transport capacity budgets (e.g., available flights, time slots, or utilization limits per zone or corridor). This yields a robust guiding plan that addresses global objectives without overburdening the operational level with overly fine-grained detail decisions. Building on this,

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the *online control* handles short-term sequencing and the concrete assignment of transport tasks to UAVs. It reacts to disruptions in an event-driven manner and new information (e.g., resource failures, changed processing/flight times, battery levels) and ensures executability via conflict-free reservations, for example for takeoff/landing and handover points. The coupling of both layers is implemented via a *repair–replan* mechanism: As long as deviations can be compensated locally, repair actions are carried out at the online layer to maintain schedule stability. If, however, systematic violations of the guardrails or constraints occur (e.g., repeated due-date violations or persistent overload of individual zones), the guiding plan is updated in a rolling horizon and the global framework is adjusted accordingly. For rough-cut planning, processing and transport times are deliberately set conservatively to ensure compliance with operating constraints (capacities and due dates) even under uncertainty. To this end, upper bounds or buffered time values are used (worst-case or quantile estimates). The online control then uses the actually observed times for local adaptation and to reduce unnecessary buffers in order to avoid throughput losses due to excessive conservatism [12].

4 Route Allocation

After the *Dynamic Production Scheduling* subsystem has scheduled a *Transport Resource Allocation Plan* (see Chapter 3), which consists of a list specifying when each transport task must be at which location and which drone/agent is assigned to execute it, the **task** of the *Route Allocation* subsystem is to generate a rough route plan for the drones. This subsystem is therefore responsible for navigation and the planning of low-collision flight routes for multiple flying robots operating simultaneously within a shared airspace. The route plan considers only foreseeable obstacles, while dynamic, unforeseen obstacles during execution (e.g., humans) are handled by the *Trajectory Planning* subsystem (see Chapter 5).

The *Route Allocation* subsystem must ensure the predictability of transport processes and transport times in order to guarantee a calculable, reproducible, human-comprehensible and safe system behavior. This is necessary for two main reasons. First, it enables the *Dynamic Production Scheduling* subsystem to generate realistic schedules based on reliable transport times. Second, it is essential for ensuring safety in human–drone cooperation. This results in several requirements for route planning. On the one hand, the system must ensure consistent and predictable behavior with respect to static obstacles as well as other drones operating simultaneously in the shared airspace. On the other hand, operational safety must be guaranteed at all times so that collisions and other safety-critical interactions are reliably avoided. In addition, the planning decisions made must be transparent and comprehensible in order to enable verification, validation and, if necessary, certification of the system. Another key requirement is a high degree of reproducibility or repeatability of the route planning, such that identical input situations lead to identical planning results and guaranteed temporal usage slots of the airspace can be maintained. Finally, the subsystem should utilize the available airspace and deployed resources efficiently in order to achieve high throughput while minimizing planning and operational effort.

In the **literature**, this problem is also referred to as the Multi-Agent Pathfinding (MAPF) problem. Existing approaches can be roughly divided into two categories: centralized methods [13, 14, 15] and decentralized or agent-based methods [16, 17, 18, 19]. While centralized approaches possess a global view of all agents and plan their routes jointly, decentralized approaches rely on autonomous agents that compute their paths independently.

Centralized MAPF approaches explicitly optimize global performance objectives such as the Sum of Costs (SOC) or the maximum completion time (makespan). Although these optimization problems are generally NP-hard, algorithms such as Conflict-Based Search (CBS) and its extensions exist that are solution-complete for practically relevant problem sizes and guarantee SOC optimality [13]. A major advantage of centralized planning lies in the explicit handling of interactions between agents: conflicts are systematically identified and resolved by introducing additional constraints, resulting in constructively collision-free solutions. This is particularly crucial in environments with a high density of agents and obstacles, where delays and blockages can significantly reduce system throughput [15]. In sum-

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mary, centralized approaches are primarily superior when global optimality, safety and high throughput are decisive. This is especially true for dense, safety-critical and strongly coupled environments such as those found in the SFG. Although decentralized approaches offer advantages in terms of scalability and simplicity, these come at the cost of reduced performance, predictability and reliability. For representing material flow in a SFG, a centralized approach is therefore required.

The **proposed concept** for the *Route Allocation* subsystem in this paper is a partitioning of the airspace into multiple geometric levels (layers), analogous to commercial aviation. The deployed UAVs are assigned to different fixed flight altitudes (Figure 3). This layering offers significant advantages over planning approaches that optimize the problem globally as a whole, such as global replanning based on Jump Point Search (JPS) according to Lu et al. [20]. These advantages become particularly evident in large-scale multi-agent systems, such as the material flow in a SFG. By separating strategic coordination, conflict management and local motion planning, the predictability and controllability of the system are significantly increased, as the number of potential conflicts for trajectory planning is reduced and the collision risk is thus confined to individual levels.

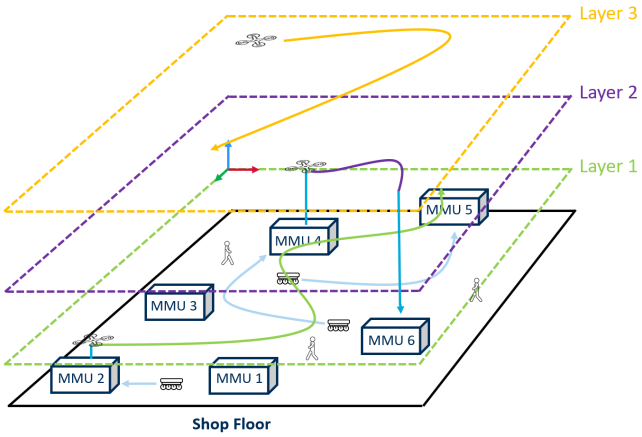

Figure 3: Sketch of the layered architecture for route planning in the SFG

The described separation of planning levels prevents local conflicts — such as the addition of a single agent or minor temporal delays — from leading to global, difficult-to-trace changes in the overall solution. Such effects typically occur in tightly coupled, globally optimizing planners. Through the layered structure, the impact of local changes remains locally confined. In addition, the partitioning into layers enables targeted fault isolation and controlled system responses. If a problem occurs, it can be handled in isolation without triggering a complete replanning of all agents. As a result, ongoing operation remains stable while simultaneously increasing the safety and robustness of the overall system. The separation also offers significant advantages with respect to scalability. In particular, it reduces the combinatorial complexity of potential conflicts faced by planners that optimize the entire system monolithically. Since conflicts only need to be resolved within individual layers, planning effort remains manageable. Moreover, the layered structure improves reproducibility and determinism of the planning process. Decisions do not arise implicitly from search orders or heuristic mechanisms, but are explicitly modeled. The decoupling of individual routes also allows guaranteed statements about the required times for individual route segments. Finally, the increased transparency of the planning facilitates formal verification and certification of the system. Because decisions are explicitly modeled and verifiable, they can be specifically validated. This is of central importance, particularly in safety-critical applications — such as the cooperation between drones and humans.

5 Trajectory Planning

The preceding subsystem *Route Allocation* handles navigation and rough flight route planning. The result is the so-called Route Allocation Plan, which specifies the flight level to be used and provides a rough route plan consisting of a sequence of a few coordinate points that the UAV should pass from the starting point to the destination. This information is not yet sufficient for the efficient use of UAVs. In order to move the UAV from the starting point to the destination point without collisions and in an energy- and time-efficient manner, detailed trajectory planning is necessary, which is the **task** handled by the subsystem *Trajectory Planning*. A conceptual distinction must be made between a path curve and a trajectory: while a path curve is a purely geometric description, a trajectory is time-parameterized.

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A trajectory thus contains information about the velocity and acceleration at each point along the path and can therefore also be optimized for these variables.

Due to their high practical relevance, there are numerous methods for path planning for mobile robots in the **literature**, that can also be applied to UAVs. These can be divided into global, local and hybrid approaches.

Global methods aim to calculate a complete path curve for the robot from a starting point to a defined destination, taking into account the entire environment. These methods are particularly suitable for planning over long distances or in static environments where the robot does not have to react to unforeseen changes. The goal of global methods is to find a globally optimized path curve that is as efficient as possible while taking into account all obstacles and restrictions. Due to this challenging objective, global methods are relatively computationally intensive. Well-known examples of global methods include Rapidly Exploring Random Trees [21] and Probabilistic Roadmaps [22].

In contrast to global methods, local methods focus on the robot's immediate environment. Local planning is more dynamic, as it must continuously respond to unforeseen changes in the environment (e.g., unexpected obstacles, sudden movements of objects or robots). The goal of local planning is to ideally respond to changes in real time and generate a collision-free path. Due to the short time horizon, local methods are designed to be significantly more computationally efficient. However, they are not able to calculate optimal path curves and are particularly prone to getting stuck in local minima. Well-known examples of state-of-the-art local methods include the potential field method [23] and the vector field histogram [24].

Hybrid methods aim to adapt an initially collision-free global path curve to unexpected obstacles. Well-known examples from the state of the art include the elastic strips method [25] and the elastic bands method [26]. The curve flow method [16] also belongs to this class of path planning algorithms.

The state-of-the-art methods listed above are classic path planning methods that do not provide any dynamic information. Building on the well-known work "Minimum snap trajectory generation and control for quadrotors" by Mellinger and Kumar [27], more and more methods for trajectory planning for UAVs have emerged in recent years. Due to the time parameterization of a trajectory, application-specific target variables (e.g., energy consumption, flight time) can be optimized while simultaneously taking into account the physical limits of the executing flight robot (max. speed, max. acceleration). In these approaches, the problem of trajectory planning is formulated as a constrained optimization problem, usually as a quadratic optimization problem. Due to the advantages mentioned above, we are also pursuing this approach.

For economic and ecological reasons, it is necessary to select trajectories for the UAVs in the SFG that are as time- and energy-efficient as possible. At the same time, for safety reasons, it is imperative that the UAVs are able to react to unexpected obstacles. According to the current state of research, the requirement to determine the most optimal trajectory possible while ensuring high reactivity and computational efficiency is difficult to reconcile. Therefore, we **propose a concept** of a two-stage approach for trajectory planning in a SFG according to Figure 4.

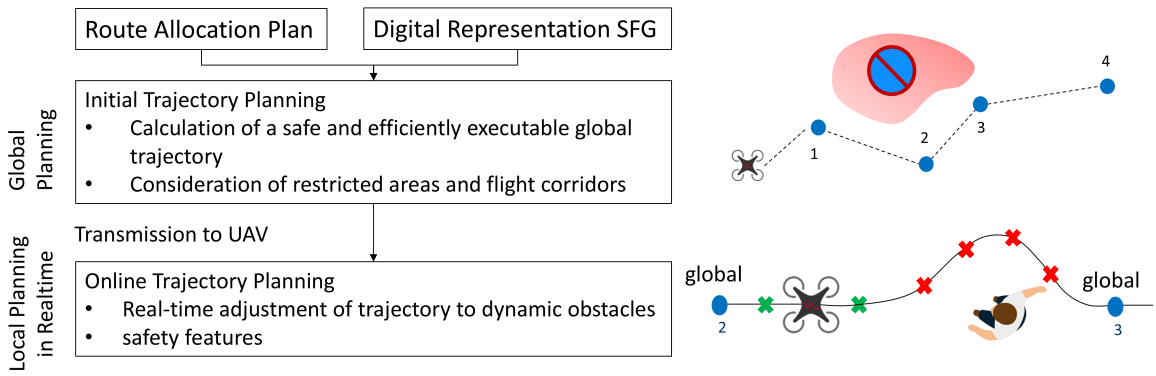

Figure 4: Two-stage trajectory planning method for UAVs in SFG

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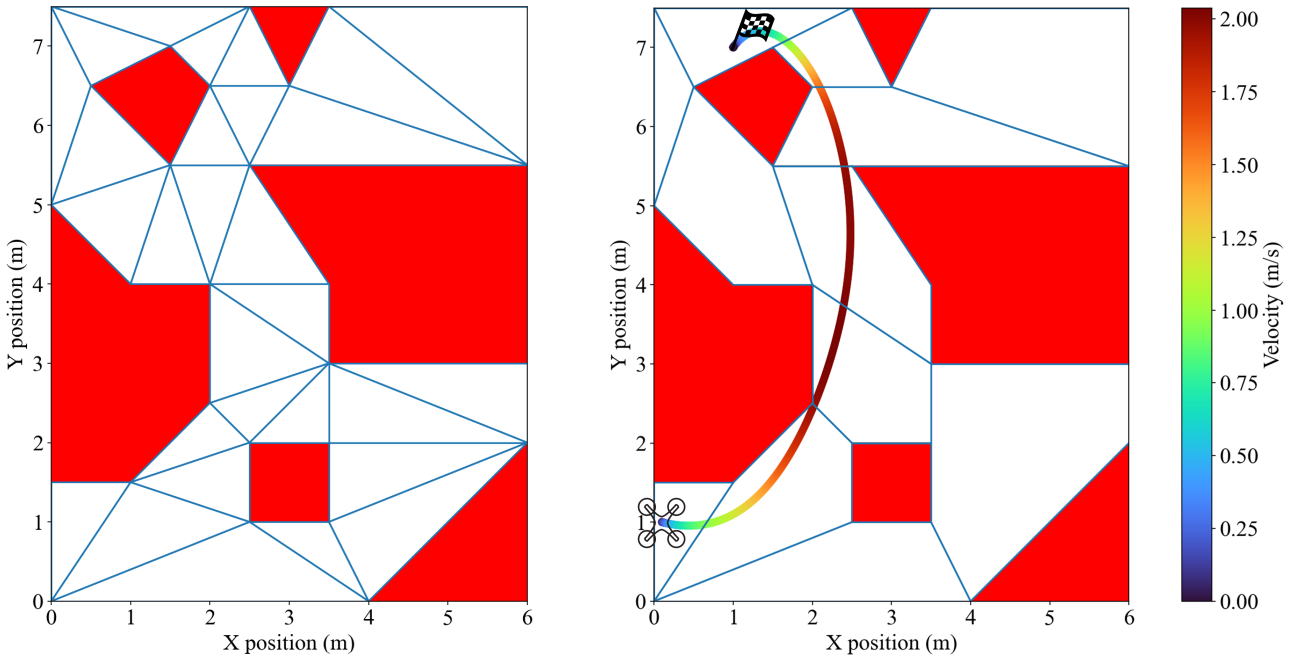
The higher-level *Route Allocation* specifies a fixed flight level in which the UAV is allowed to move. Trajectory planning is therefore carried out in a two-dimensional plane. In addition, a sequence of coordinate points that the UAV has to pass is specified, as well as permissible flight areas and flight corridors that the UAV is allowed to use. In the first step of the two-stage trajectory planning process, the best possible global trajectory is calculated while complying with all given boundary conditions. This is done before takeoff. In addition to the spatial constraints specified by the *Route Allocation*, the dynamic limits of the UAV (max. flight speed and max. acceleration) must be taken into account. This is the only way to ensure that the planned trajectory can actually be executed. To meet these requirements, we propose an approach to global trajectory planning based on Bézier splines. In a first geometric preprocessing step, we first triangulate the available flight space of the flight plane (see Figure 5 (a)) and then form the largest possible convex polygons from it (see Figure 5 (b)). Obstacles can be approximated by arbitrarily shaped polygons (shown in red in Figure 5). A sequence of convex polygons is then determined that connects the start and destination points. A Bézier spline segment is fitted into each of these convex polygons to create a continuous trajectory from the start to the end point (see Figure 5 (b)). A Bézier spline is mathematically defined by a weighted sum of control points (not shown in the figure), whereby the spline always passes through the first and last control point. Bézier splines have the special property that the course of the spline always lies completely within the convex polygon spanned by the control points. We deliberately use this so-called convex hull property for collision-free trajectory planning. By appropriately selecting the boundary conditions when formulating the optimization problem, we ensure that the control points of a spline segment always lie within the convex polygons that were determined as obstacle-free areas during the geometric preprocessing step. This ensures that the entire trajectory is collision-free. The majority of state-of-the-art methods cannot provide this analytical proof. Instead, the collision-free nature of the trajectory is only checked at discretized points. Another significant advantage of our method is that we can approximate obstacles with arbitrarily shaped polygons. Many state-of-the-art methods only allow simple primitives such as spheres, cylinders, or planes to represent obstacles.



(a) (b)

Figure 5: Division of the free flight space into convex polygons for subsequent trajectory planning. The obstacle polygons are marked in red. (a) Initial triangulation of the flight space. (b) Optimized division in convex polygons and optimized trajectory.

Once the first step of the two-stage trajectory planning process has been completed and an optimized global trajectory has been determined, it can be executed. In the highly dynamic production environment of a SFG, it is to be expected that the originally planned trajectory may be disrupted at any

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time by unexpected, dynamic obstacles (people, industrial trucks, etc.). Therefore, a downstream reactive online trajectory planning method is required that monitors the execution of the pre-planned trajectory and adjusts it if necessary. In reactive trajectory planning for autonomous UAVs, the trend is increasingly moving toward Model Predictive Control (MPC) and learning algorithms. In MPC, the future trajectory of the UAV is calculated by solving an optimization problem, taking into account the system model and boundary conditions. These algorithms enable the UAV to react flexibly to unexpected changes in the environment in real time. A prerequisite for the good performance of these algorithms is precise modeling of the system and the environment. Learning algorithms, in particular deep learning and reinforcement learning, offer the advantage that, due to their data-driven approach, they can also handle complex systems that are difficult to model mathematically with precision. However, the problem remains that the behavior of learning algorithms is not deterministic, which makes it impossible to provide a proof of safety. For the use case outlined here in a SFG, however, safety and traceability play a central role. Therefore, our research activities will focus in the future on MPC for reactive trajectory planning.

6 Conclusion

This paper presents a concept for designing highly flexible material flows in a SFG that leverages the use of UAVs as a central component of intralogistics. By combining three specialized subsystems — *Dynamic Production Scheduling*, *Route Allocation* and *Trajectory Planning* — a dynamic, multi-criteria optimized scheduling and control system is realized that is intended to meet the requirements of modern, individual production. The proposed architecture enables efficient coordination of production processes and material flows while considering time, cost and energy objectives, with particular emphasis on safety, reproducibility and plan stability.

In particular, the hierarchical structure of route and trajectory planning based on a layered airspace architecture represents a significant improvement over other planning approaches (see, e.g., [13, 15, 17, 19]). Centralized coordination in the Route Allocation subsystem ensures collision-free, predictable and comprehensible flight routes, while the reactive trajectory planning in the *Trajectory Planning* subsystem enables a high degree of flexibility in the presence of dynamic disturbances.

The presented concept highlights the significant potential of UAVs to substantially increase the flexibility and dynamics of existing intralogistics systems in a SFG. In doing so, key challenges such as the coupling of production and transport, safety in shared airspace and scalability in highly dynamic environments are addressed. Consequently, the concept contributes prospectively to the realization of a future-oriented, resilient and autonomous manufacturing system. Future work will focus on the further elaboration and concretization of the concepts described in this paper.

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