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Adaptive AGV fleet management in a dynamically changing production environment

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Abstract

In the era of smart manufacturing, autonomous mobile robots have become affordable for numerous companies, although the fleet management remains a challenging problem. A novel approach is proposed, supporting the solution of vehicle assignment problem. The method relies on adaptive workstation clustering that considers not only complex environment layout, but also the main characteristics of the material flow. The technique combines network analytical and optimization tools with a greedy algorithm of refinement. The implementation is presented, and the impact of clustering techniques on selected performance metrics are analyzed within a series of experiments, taken from an industrial case study.

Keywords: internal logistics; AGV; network; modularity; MIQP

1. Introduction

Production and logistics, though inseparably integrated and interwoven as far as the flow of material is concerned, are clearly distinguished in terms of their goals. While production is responsible for meeting external market demand by performing value-added activities, *internal logistics* has to see that all material conditions of these activities are satisfied all the time. Albeit indirectly, logistics has a definite impact on the key performance indicators (KPIs) of production, such as service level and delivery performance, resource utilization, throughput and lead time, as well as cost. The ideal logistics serves production in an "invisible" way, by making the required materials, components, parts, tools and fixtures available for the primary production resources, and, at the same time, by making the same resources free from the results and by-products of their activities. Logistics, consequently, has to adapt to changes in production, let they be planned or unpredictable, long-term or imminent [8, 9].

This work was motivated in particular by the specific needs of the *semiconductor industry*, where advanced planning and scheduling of even the primary production resources poses some extreme challenges. Here production operations take relatively long but often uncertain times, process routings are re-entrant, some tight temporal constraints must be observed due to the risk of contamination, while the in-process buffer sizes are strictly limited. The main KPIs are to maximize resource utilization, and, simultaneously, to minimize the throughput time of orders [6]. It is generally accepted that production in such a complex, dynamically changing environment burdened both by product and process related uncertainties can only be controlled by some dispatching logic which adapts to the actual situation at hand and decides in real-time but only on the short term what and where to do [10]. Logistics should flexibly accommodate to this mode of operation. No wonder, *automated guided vehicles* (AGVs) are predominant when providing internal logistics service for this industry.

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AGVs are versatile, driverless, free-ranging transport devices with localization and autonomous control faculties [4]. They operate usually in a fleet, carrying loads of multiple types and cardinality. Recently, their application in different industrial settings has proliferated [2], and one can expect an even more intensive expansion of their use with the advancement of reconfigurable and changeable manufacturing technologies on the one side, and of autonomous vehicle techniques on the other side.

We were aimed at providing an internal logistics AGV service for a complex, large-scale production environment where processing times are fraught by uncertainties, changes in order priorities as well as interrupts and re-entrant work may happen any time. In face of all these difficulties, a smooth flow of materials had to be warranted, so as to maximize ultimately the utilization of production resources. In any case (and at any cost), the AGV service should not be made accountable for blocking production either by shortage or by the accumulation of material.

Following the recommendations of the literature on the state-of-the-art [2], a *hierarchical decomposition* approach was taken to the above AGV fleet management problem [7]. First, on the strategic level, the material flow network model of the production facility was decomposed into clusters, or *zones*. Next, on the tactical level, AGVs were assigned to the zones so as to balance their expected load. Finally, on the operational level, appropriate *dispatching* rules combining distance- and time-based metrics decided about the actual assignment of vehicles to logistics tasks. After extensive simulation studies, elements of the overall approach have already been deployed in a large-scale real industrial environment, with unanimous success [6].

In our understanding, this workflow not only reduced the complexity of the fleet management problem, but also prepared the ground, with appropriate planning decisions covering a longer horizon, the efficient application of otherwise short-sighted dispatching rules. The formation of zones was done by performing a so-called *graph modularity* analysis over the network model of the production system which is comprised of the material flow data collected in a longer past period. One could deem this analysis an *unsupervised learning* over past (big) operational data of the production system, which detected the hidden, internal structure of the material flow. This structure could then be exploited by AGV assignment and dispatching. Learning in this sense could contribute to the most advanced, *prescriptive use* of *big data* [12]. However, in a continuously changing production environment one-shot learning is rarely sufficient; one should rather observe the ”digital exhaust” of the system continuously, and adapt its control – in this case, the management of the AGV fleet – to the evolving conditions time and again [13].

This paper investigates whether and how our hierarchical AGV fleet management workflow can adaptively be applied under changing work conditions. After exposing the problem (Sect. 2), Sect. 3 introduces the basic concepts and phases of the workflow, with an extension of refining the AGV assignment to changing workload. Specifically, we use data accumulated in the recent production period to evaluate overall system performance and to decide, whenever needed, on the revision of AGV assignments. Detailed computational experimental results presented in Sect. 4 show a comparative advantage of the new method. Finally, Sect. 5 gives a short outlook to future works and concludes the paper.

2. Problem statement

The system under study consists of a set of *machines* and *buffers* as active material processing and passive storage *stations*, respectively, and an *AGV fleet* that transports the items among them in a completely automated way. Items are considered to be general container units of standard size, capable of holding any kind of input/output material of production. The AGVs are identical and can carry multiple items up to their maximal capacity. The flow of materials is determined by the routing, which defines the logical links among the stations, the layout of the shop-floor and the actual workload of the production system. Any link in the routing can be realized by alternative paths in the layout which imposes physical constraints on the movements of vehicles. Hence, paths can be one- or bidirectional, narrow or broad. Internal transport is subordinated to production: stations generate time and again requests to the AGV fleet in terms of *tasks*. Each task is specified by (1) the item to carry, (2) its type which is either delivery or pickup, and (3) its destination or source station, respectively. A machine can only start its operation after the related AGV tasks are finished, hence, waiting times due to shortage or accumulation of materials are direct losses accounted to the AGV system. It is assumed that information about tasks are accessible for each vehicle.

Given the above constraints and the dynamically incoming stream of tasks, the AGV fleet as a whole is responsible for providing a transportation service which accomplishes each task in a way that minimizes total losses on a given horizon. In a saturated system typical in semiconductor industry, this implies the objective of maximizing the utilization of active machine stations. Additional KPIs include the total number of AGV tasks completed in a given period of time, as well as the average task duration that spans between the task triggering and finishing time points. As for the functions required for supporting the physical operation of vehicles like localization or collision avoidance, it is assumed that execution monitoring and control is capable to do these, whereas the workflow suggested below greatly alleviates the prevention of collisions and deadlocks.

3. Methodology

The solution of the above problem consists of (1) finding an initial appropriate assignment of AGVs to tasks, and (2) refining this assignment over time. Since tasks are generated on the fly, the solution process would fit into some online scheduling or dispatching scheme [2]. However, meeting the requirements detailed in Sect. 1 calls for a broader perspective and a longer horizon where AGV fleet planning with some look-ahead prepares the ground for the right dispatching decisions. The core idea is to find and exploit the hidden structure of the overall material flow. Hence, a novel network model is suggested to capture the flow of material over a given horizon. This represents also the physical proximity of the stations. Departing from this model and the specification of a given AGV fleet, the workflow goes through the following phases (see also Fig. 1):

1. *Network analysis* finds non-overlapping clusters where the flow within clusters highly dominates the flow between clusters.
2. *Load balancing* assigns vehicles of the AGV fleet to the zones in such a way that sufficient logistics capacity is provided to each zone, and the expected load of vehicles over the planning horizon are balanced, as far as possible.
3. *Online dispatching* assigns—with a limited scope defined by each zone—vehicles to the dynamically generated tasks and determines their execution sequence.
4. Performance of the AGV management system is monitored continuously, and if the value of some critical KPI outruns its acceptable range, then the assignment model is updated greedily.

    (a) The best and the worst assembly workstation zones are identified based on certain performance parameter(s).
    (b) The AGV with the least utilization is identified from the best zone's set of AGVs.
    (c) The AGV in question is relocated to the zone with the worst performance parameter.

The substeps of step 4 are repeated over time. This refinement sequence of actions is activated automatically when a certain set of KPIs does not reach a preferable level. In some cases it is advised to define a minimum length of time before starting the refinement loop, since complex production systems require ramp up time to achieve a stable state. The length of the ramp up time depends on the characteristics of a given production system, a general rule is to wait until (1) a steady state of the system is achieved and (2) necessary and sufficient amount of data can be collected. Fig. 2 shows the sequence of steps over time.

The principle of aggregation is applied in two senses: initially, many details are disregarded (e.g., in the first step even the specifics of the AGV fleet) but the horizon is relatively long. However, as one gets closer to execution, the horizon is shortening while the model corresponds more and more the real execution environment. This helps not only to decrease decision complexity considerably, but also to respond to the uncertainties which inherently burden production, and thus, consequently, the management of its internal logistics, too.

3.1. Network analysis

The initial problem is represented in terms of a network which captures main properties of the layout. *Nodes* of this network are the stations, whereas directed and weighted *edges* stand for the routes between stations. The weight of any edge

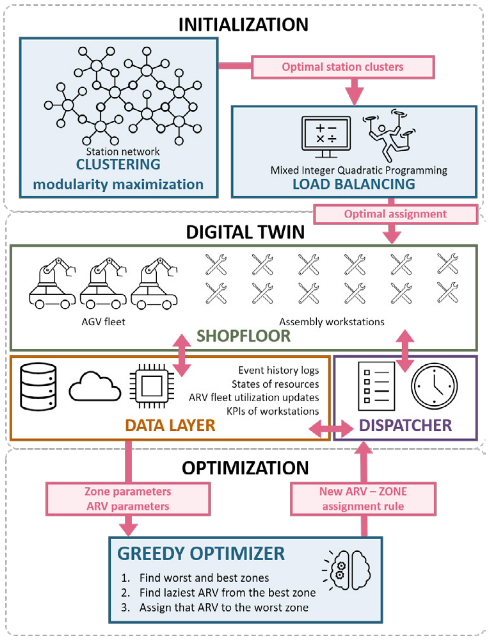

Fig. 1. Structure of workflow. The first step (initialization) serves as a setup of the environment. The middle part (digital twin) remains intact during the whole process of refinement. Finally, the optimization step is repeated over time and sends updates to the dispatcher in the hope of a better performance.

Fig. 2. Sequence of methodology over time. Initialization is performed only once before the first simulation run. A trigger (e.g. insufficient KPI values) stops all active processes, and the refinement optimization process starts. Its results are sent back to the dispatcher and production is continued with the new input.

is inversely proportional to the distance of the shortest path between the corresponding nodes. There is no distinction as for the specific items transported, neither in the timing nor in the distribution of transport tasks over time. Between two nodes there could be two different edges, one in each direction. Note that the AGV fleet is not part of this initial model.

The *distance network* is the input for an analysis which is aimed at finding an internal structure of the problem. This structure is the basis for the decomposition of the networks' stations into non-overlapping clusters. As it is expected, confining the movement of AGVs to single clusters and minimizing inter-zone traffic will not only improve the performance of the system but also alleviate the issues of collision and deadlock avoidance. However, since neither the size nor the number of clusters are known a priori, traditional methods of graph partitioning or clustering cannot be applied here. Instead, a recent concept of network science, *graph modularity*, is adopted for characterising and finding a good division of the distance network.

Modularity was originally introduced to capture the community structure in networks [1] [11]. Albeit it is still broadly investigated [3], there is a consensus that it reflects such a decomposition of the network where (1) the links between clusters are not only few, but fewer than expected, and (2) the fraction of these links are dominated by the fraction of inter-cluster links. This notion developed for standard graphs is tailored here to the distance network with directed and weighted edges. However, if there are valid routes between every station pairs then the distance matrix is a full directed and weighted network, so edge reduction is very much endorsed by deleting links between nodes that are relatively far from each other.

Formally, let $V = \{v_i\}_{i=1}^{N}$ be the set of stations and A the adjacency matrix with weights $A_{ij} = \frac{\max d_{ij}}{d_{ij}}$ of edges from v_i to v_j, where d_{ij} is the length of the shortest route from v_i to v_j if $i \neq j$ and $A_{ii} = 0$ for all i. This way all edge weights are at least 1, and smaller distances have higher edge weights. The outdegree and indegree of node v_i are noted as k_i^- and k_i^+ respectively, while the sum of all edge weights is m.

The modularity of a clustering C of the weighted and directed graph is defined as

$$Q(C) = \frac{1}{m}\sum_{ij}\left(A_{ij} - \frac{k_i^- \cdot k_j^+}{m}\right)\cdot \delta\left(c_i, c_j\right), \qquad (1)$$

where c_i and c_j are the zones of v_i and v_j nodes respectively, and δ is the *Kronecker-delta* function [7]. Modularity quantifies the strength of a division, measures the relative density of edges inside communities with respect to edges outside communities. In contrast to other clustering methods, modularity maximization can detect not only the optimal membership but also the optimal number of clusters. Identifying the strongest clustering on the nodes of a network is identical to finding C^* clustering which maximizes the $Q(C)$ modularity function.

3.2. Load balancing

The AGVs' workloads are aimed at balancing uniformly, in order to best utilize the fleet capacity and properly serve the machines. The *load balancing model* that defines the AGV-zone assignments is formulated below as a mixed integer quadratic problem (MIQP). In this problem, the cycle times of the machines are assumed to be known, and they define the average time that an item is spending on a station while being processed. Formally, let us denote the set of AGVs as $\mathcal{A}$, the set of clusters as C and the set of stations as V (referring to the nodeset of the distance network). Using this notation, the MIQP of load balancing can be formulated as:

$$\text{minimize} \sum_{v\in V}\left(\sum_{a} X_{v_c a}\cdot\frac{1}{CT_v}\right)^2 \qquad (2)$$

$$\text{subj. to:} \sum_{a} X_{ca} > \beta_c \qquad \forall c \in C \qquad (3)$$

$$\sum_{c} X_{ca} > \alpha_a \qquad \forall a \in \mathcal{A} \qquad (4)$$

$$X_{ca} \in \{0, 1\} \qquad \forall c \in C, \forall a \in \mathcal{A} \qquad (5)$$

In the above model, X_{ca} is the indicator of assigning AGV a to zone c, v_c is the cluster of station v, CT_v is the cycle time of station v, $\alpha_a \geq 1$ is the minimal number of zones that AGV a is assigned to, and $\beta_c \geq 1$ is the minimal number of AGVs assigned to cluster c. These parameters must be tuned for every individual MIQP regarding to the feasibility of the given problem. Minimizing the objective function (Eq. 2) is equivalent to balancing machine-AGV assignments based on their cycle times. All the constraints are necessary for having a valid AGV-zone assignment. Eq. 3 ensures that every station cluster gets at least β_c different AGV(s) to serve them. Without this constraint it might happen that a cluster of stations does not receive any AGVs. The same explanation holds for Eq. 4. The last constraint (Eq. 5) is technical, it symbolizes the fact that any AGV is either assigned to a certain cluster or not.

3.3. Dispatching

On the dispatching level of the decision-making hierarchy, tasks are assigned to vehicles, assuming a saturated system where machine stations are continuously triggering tasks. Every AGV maintains its own list of assigned tasks and their execution sequence is determined by the dispatcher. The proposed distance- and time based (DTB) dispatching approach is dynamically switching between so-called delivery-task-first and pickup-task-first rules [2]. Motivated by maximal vehicle utilization, the assignment of delivery tasks starts only after the AGV is already fully loaded, or no open pickup task is remaining. An AGV completes all the assigned deliveries until it becomes empty, then starts to pick up items again. The prioritized task type is registered in some parameter. Considering the task assignment triggers, vehicle initiated rules are more commonly applied in saturated systems where AGVs rarely wait. Whenever a vehicle completes a task, the following procedure is executed to find the next task. The details of the used dispatching logic are described in [7].

3.4. System refinement loop

Real life production systems are not free from random events, unwanted failures or unpredictable breakdowns. The pattern of workload can also change in time. Hence, these systems have ever-changing environment state, therefore the refinement of the dispatcher's input is essential for maintaining a valid and close-to-optimal operation. The method of refinement can easily get over-complicated, since the external environment is usually a very complex one. Hence, it is advised to work with simple models to apply simple modifications at a time, as even small changes can cause significant differences in the operation of complex systems. The proposed refinement loop is indeed such a greedy reallocation of AGVs between some selected zones. Despite of its quite straightforward algorithm, its positive impact on the main KPIs of production is clearly visible in the next section.

The main idea of the *refinement loop* is to reallocate only one AGV at a time. The reallocation shall be done from the best station cluster to the worst one. The level of *goodness* can be measured in many ways, most commonly used metrics are availability, utilization or quality. Let us now define a new metric of goodness, which shall be the combination of performance and availability. Performance is described by the number of assembled (done) parts. The other ingredient will be the number of *potential* parts. A potential part is a part that could be assembled if the machine station were fully served by the AGV fleet. A potential part comes from the time period(s) when the station waits for new parts to assemble or when the station cannot start working on a new part because the old part is not yet shipped (i.e. the station is blocked).

Mathematically speaking, the number of *potential parts* are the fraction of unused time (waiting plus blocked time) and cycle time (Fig. 3). The measure of goodness is defined as the fraction of potential parts and assembled parts. This fraction literally shows what percentage of the assembled parts could have been done in case of a perfectly served station. Of course this value is highly unlikely to be reachable: it can be easily seen that any AGV fleet has its limits in serving. Also, installing more vehicles might result in higher number of assembled parts, but a new AGV can bring at least two disadvantages: (1) autonomous vehicles are quite expansive resources, and (2) bigger fleet means more frequent and heavier traffic jams on the shop-floor. Therefore it is not quite practical to solve performance problems simply by adding/purchasing new AGVs.

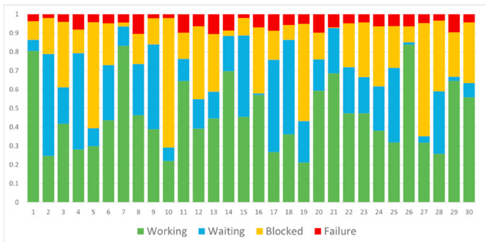

Fig. 3. An example for assembly station state deviation. Each bar represents one assembly station. Number of *done parts* is the green area multiplied by passed time and divided it by the station's cycle time. Number of *potential parts* is defined as the sum of blue and yellow area multiplied by passed time and divided by the station's cycle time.

The defined measure of goodness (potential ratio) can be used not only for single assembly stations, but also for set (clusters) of stations or even for the whole production system. In case of clusters, the potential ratio is defined as the fraction of (1) the sum of potential parts of all stations in the cluster and (2) the sum of assembled parts of the same set of stations.

One question remains open: which AGV should be reallocated from the best to the worst zone? (Let us note that this question is only appropriate if the best cluster has more than one AGV assigned.) To be able answer the question it is necessary for the AGVs to be comparable. Of course the best logic is to send the most useless AGV to the new zone. The most useless AGV can be the one that spent the most time in the parking area or the one that has the lowest number of completed task per driving distance ratio. It is up to the user how to define usefulness.

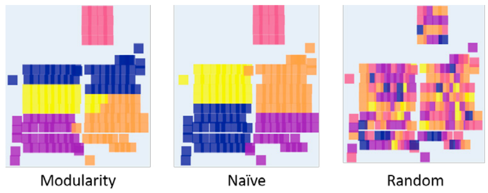

Fig. 4. The heatmaps of the three different assembly station clusterings.

This refinement of the AGV-zone assignment is investigated in the following section, where different zoning methods are compared via simulation experiments, and the effects of periodic refinement are discussed.

4. Experimental results

The effectiveness of the complete workflow is demonstrated here via experimental results, taken from a large-scale industrial case study. The discrete-event simulation model (with a 95% validated accuracy) of the real system was used as a testbed of the experiments [6]. The system consists of nearly 200 machines and 17 AGVs with the capacity for transporting at most five items. The assembly stations have varying cycle times (2 - 7 hours) based on the technological requirements of the processed job. Assuming a saturated system throughout the experiments, the main objective was to maximize machine utilization by efficient AGV fleet management.

The layout of the shop-floor is somewhat special, it consists of a main rectangular section and a smaller island (Fig. 4). First, three different clustering methods are compared: modularity-based, naïve and random clustering. Modularity is described in Sect. 3.1. Naïve clustering assigns the machines of the island to a separate cluster, and it splits the main area into four clusters of the same size. Random clustering assigns a cluster label randomly to each assembly station.

Next, simulation experiments were run over a horizon of two days to test the three zoning models. For each model 20 independent experiments were performed, and their performance was compared through the total number of completed AGV task. Fig. 5 shows the results. It should not be surprising, that random zoning brings the worst results with the highest standard deviation. The mean values of modularity-based and naïve clustering are not very far from each other, but the later has much less stability. From now on random clustering is dismissed, the focus is on comparing the first two separations.

In the following experiments, 20 rounds of AGV assignment refinement were completed on both the modularity-based and naïve clusters. The ramp up time of the system was set to 2 days, meaning that refinements cannot happen before this period. When the ramp up phase was passed, the system was automatically triggered if the utilization of AGVs was unevenly distributed or if their performance dropped below a certain threshold. In Fig. 6, the evolution of total completed tasks shows how reallocating AGVs improves the system's overall performance. Two unexpected valleys can be identified in case of naïve clus-

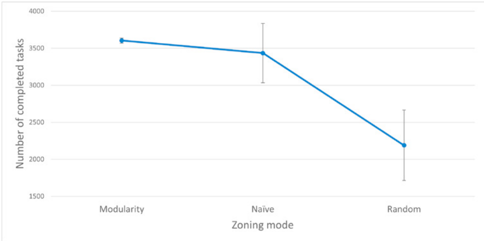

Fig. 5. Performance of the three clustering methods measured by the number of completed AGV tasks. The middle points show the average values of 20 independent experiments (each mode), the width of whiskers are proportional to the samples' standard deviations.

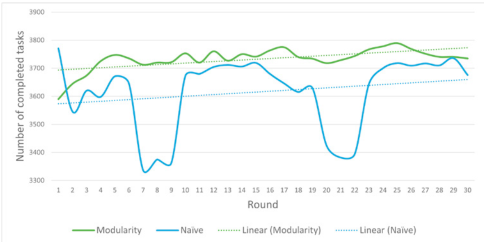

Fig. 6. Effect of multiple refinements on two different zoning methods on number of completed AGV tasks and its trend.

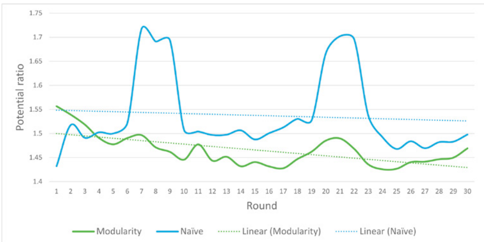

Fig. 7. Effect of multiple refinements on two different zoning methods on the ratio of potential and done parts and its trends.

tering. This phenomenon refers to the higher system instability which was already discussed above.

Also, the previously defined potential ratio shows improvement over refinement (Fig. 7). The two figures are nearly reflections of each other, which is a direct result of their connectivity: more completed AGV tasks mean more assembled parts and they are followed by lower potential ratio.

5. Conclusions

In the paper, a new AGV fleet management approach was proposed that benefits from the analysis of the overall distance network, and refines the production system model with a greedy AGV reallocation. The proposed modularity-based clustering detects the subsets of stations with strong dependencies, without the need of declaring the expected number of zones. In this way, the adaptability of the overall solution can be guaranteed, as the network model can be updated from time to time when changes in the material flow requires that. On the dispatching level, the method is capable of responding to the specific needs of production control (i.e., dispatching with time windows even under uncertainty [5], or considering AGV as buffers as well). Considering the maximal utilization of machines as a key criterion of AGV fleet operations, even in case of complex production and logistics systems, the proposed refinement method results in significant improvements, compared to conventional approaches that rely purely on spatial or time attributes.

Based on current outcome in the topic, future research is highly motivated. An interesting path would be the implementation of the initialization part into the refinement loop (Fig. 1), namely the effect of adaptive station clustering and AGV workload balancing. Although that would require a higher computation capacity than the current greedy optimizer, a better production output is expected.

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