Conceptual Design of a Decision Support System for Material Flow Planning and its Transfer to Public Transport

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1. Motivation

The trends of increasing value creation, customer orientation, sustainability, and digitalization are putting manufacturing companies under increasing pressure. Existing, established production and logistics systems can no longer fully meet these additional requirements regarding flexibility and dynamics. Inefficient and non-transparent material flows arise. Currently and in the future, most material transports are done manually (e. g. using forklifts). Challenges such as long throughput times, poor utilization of transport systems, and long transport distances result. To achieve economic, technical, organizational, and sustainability objectives, manufacturing companies are faced to optimize these weaknesses. Therefore, material flow planning is performed (Pfohl 2023; Chakraborty/Saha 2022; Berndt et al. 2021; Dickmann 2015). Concept planning is the first planning phase. It includes the identification of potentials, the development of different technical concepts, and the preparation of decisions for the selection of the preferred one (Martin 2016; VDI 2498 Part 1 2011). However, problems arise when performing material flow planning due to poor data quality, missing data, and complex decision-making. In many cases, these lead to one-dimensional, isolated, and suboptimal planning results and high efforts for planning (Burggräf et al. 2021; Dickmann 2015).

The reasons are outdated and qualitatively insufficient data without reference to actual processes (Hosseini-Nasab et al. 2018), errors in the double-digit percentage range in data from IT systems (Dickmann 2015), high efforts for data procurement (e. g. interviews, observations) (VDI 2689 2019), untapped potential of digitization solutions such as sensors (Hayward et al. 2022), and a lack of decision support in planning (Burggräf et al. 2021).

Therefore, this paper aims to develop a concept for a decision support system for optimizing forklift material flows based on sensor data. On the one hand, the efficiency and the data-drivenness of material flow planning shall be increased. On the other hand, this decision support system provides the mathematically optimal result regarding the layout arrangement of sources and sinks, the forklift deployment and the order allocation, and the selection of optimal forklift types including

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proven automation. This should contribute to reducing logistics and material flow costs in manufacturing companies. In addition, the transferability of this concept to public transport is to be evaluated. This should determine to what extent industrial management methods can be used outside of factories and how these methods contribute to creating a sustainable future.

To achieve these aims, the following structure is chosen for this contribution. Section 2 discusses related work of sensor-based decision support in logistics and decision support systems for material flow planning. Based on these related works, a sensor-based concept of a decision support system for optimizing internal forklift material flows in manufacturing companies is developed and discussed in section 3. Since the logistics challenges on the last mile are like those of internal material flow, section 4 provides an outlook on the transferability of this in-plant concept to crowdsourcing delivery using public transport. This is done during the Öffi-Packerl research project. Finally, the results are summarized and an outlook on further research is given.

2. Related Works

As discussed in section 1, the complexity and dynamics of logistics and material flow are continuously increasing. Making correct and forward-looking decisions in planning processes to minimize consequential costs and additional efforts is becoming increasingly important (Ben Rabia/Bellabdaoui 2022). Amulu Priya et al. (2021) state that using operations research methods is necessary to achieve data-driven, efficient, and analytical optimization of logistics processes. For this purpose, the logistic decision problems are modeled mathematically and solved using exact calculation methods, heuristics, multi-criteria decision-making (MCDM), and simulations (Yazıcı et al. 2022).

- Linear programming is an exact method to calculate an optimum under constraints. Types of linear programming are integer, dynamic, and goal-oriented linear programming.

- Heuristics are used when problems cannot be represented using exact calculation methods or the calculation is too time-consuming. These methods provide results close to the optimum and can be implemented globally as a meta-heuristic or locally as problem-specified optimization.

- MCDM supports the solution of multiple decision problems when different solution variants and alternatives exist and an optimally suitable one is to be selected. MCDM are classified into benefit-based and superiority-based methods with various characteristics.

- Simulations model the properties of systems using parameter variations and support decision-making, as impacts on the existing system can be evaluated before a new, adapted, or revised system is introduced (Yazıcı et al. 2022).

2.1. Sensor-Based Decision Support System

Decision support systems (DSS) are computerized information systems to support management decision-making (Yazdani et al. 2017). Such Systems consist according to Ben Rabia and Bellabdaoui of three interacting layers (2022): data, model, and knowledge layer.

- The data layer collects, manages, and prepares the database for solution finding, which includes structured (e. g. ERP data), semi-structured (e. g. sensor data), and unstructured data (e. g. text or image files).
- The model layer solves complex problems and provides a toolbox of operations research and simulation methods.
- The knowledge layer prepares the knowledge generated by the system for decision-makers using mathematical models and data analysis.

A DSS requires knowledge of the current and future status of the decision-making system. This includes orders, resources, entities, and processes. An inadequate database and a low real-time reference make decision-making difficult (Korth et al. 2018; Marinkovic et al. 2023). Therefore, the importance of real-time information is increasing. Sensors and Internet-of-Things applications are used for this purpose (Ben Rabia/Bellabdaoui 2022; Coelho et al. 2021). First, sensor-based decision support systems have already been discussed in related works. Estanjini et al. (2011) use a sensor network to optimize forklift dispatching. The data regarding duration of use, collisions, battery level, and position of the forklifts are collected based on sensors. The generated and processed data is then used in a decision support system that uses heuristics to optimize the forklift dispatching. Müller et al. (2018) develop a decision support system for an industrial laundry to schedule picking and transport orders optimally in real time. RFID (Radio Frequency Identification) tags are attached to the laundry to track its location. Booking data is used to identify the vehicle's position. In the simulation-based methodology of Kibira et al. (2015) to support the planning of manufacturing processes, data input is based on sensors. Ecker et al. (2023) show that sensor-based material flow planning can optimize sustainability criteria of manufacturing companies such as energy efficiency besides economic ones.

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2.2. Decision Support for Material Flow Planning

The following section summarizes related works that provide decision support in material flow planning. The authors consider the areas of order allocation of transports, selection of transport systems, automation of transport systems, and layout planning. Sensors are not used for data collection in these works. In Coelho et al. (2021) and Carli et al. (2020), additional real-time information through sensors is specified as a need for further research.

Carli et al. (2020) develop a decision and control model to assign transport tasks optimally to electric forklifts. The aim is to save costs and energy. A heuristic consisting of two phases is applied, combining the optimal job while respecting the queue of orders, the battery charging process, and the replacement schedule. Korth et al. (2018) describe an architecture model of a simulation-based digital twin for decision-making in intralogistics optimization. ERP systems act as the data basis. The model is intended to guide the planner and to generate partially automatic scenarios. The authors describe several potential areas of application, such as layout planning, technology selection, or order planning, in which the architecture model is conceivable. In a case study, the authors apply the model to optimize the shift planning of forklifts. Marinkovic et al. (2023) develop an architecture for a digital twin for optimal resource planning of internal transport systems. This is intended to improve decision-making in the planning and sequencing of transportation tasks of current and future scenarios.

In the field of selection of the optimal transport system in intralogistics, various MCDM approaches appear. The decision support systems of Chakraborty and Saha (2022), Fazlollahtabar et al. (2019), and Pamučar and Ćirović (2015) focus on selecting optimal forklifts based on criteria like the purchase price, age or working hours. Mahmutagić et al. (2021) develop a two-stage decision support system to evaluate the efficiency of the currently used forklifts and derive the optimal forklift selection based on this analysis. Zubair et al. (2019) solve an MCDM for a pharmaceutical company for selecting the optimal transport technology. Their solution approach includes a questionnaire to identify the state of the art. Then, an analytical hierarchy process is applied to choose between automated guided vehicles (AGV), conveyors, and forklifts. Rahnamay Bonab et al. (2023) support decision-making for the optimal selection of automated vehicles for freight transportation.

Coelho et al. (2021) develop a framework of a simulation-based decision support tool for the material supply of production plants. The work is intended to serve as the basis for a digital twin that can be used independently in various intralogistics scenarios. The data basis was partly collected manually, e. g. times for material handling by forklift. Kluska (2021) supports the decision-making process in the design of warehouse layouts and technical equipment.

A simulation model based on WMS data is used for this purpose. Constraints such as track widths for transport technology are considered. The planning is done automatically based on 17 steps. This automation significantly reduces the planning time compared to conventional planning.

In summary, it can be stated that various decision support systems exist for the material flow planning of internal transport systems. However, most systems deal with one-dimensional issues without holistic planning approaches. Thus, MCDM methods are used to evaluate and select manual and automated transport systems. Heuristics and simulations are used to optimize layouts and order allocation. Linear programming is very rarely used due to long calculation times. The data basis for the optimization methods usually comes from ERP or WMS systems. The data were sometimes generated using random numbers to test algorithms and procedures. The use of sensors to create real-time references is rarely applied. Therefore, some papers describe using sensors as one of the further research steps. This should enable the automation of material flow planning from data collection to decision-making, as data collection and processing currently causes high manual efforts.

3. Conceptual Decision Support System for Sensor-Based Material Flow Optimization

Based on the discussed related works, this section develops a concept of a decision support system for sensor-based material flow planning of internal transport systems in manufacturing companies. For this purpose, requirements, and restrictions for the decision support system are defined first. Based on these, the conceptual decision support system and its three layers are designed. Finally, the results are compared with the related works, and challenges for the transfer to public transport are discussed.

3.1. Requirements and Restrictions

The following requirements must be met when developing the decision support system:

- The planning content of the system shall include concept planning. For this purpose, weak points in the current material flow system are to be identified, optimization potentials are to be calculated and evaluated, and recommendations for action are to be derived and graphically prepared. This information is to be used by the company's management to determine the preferred scenario.

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- The decision support system shall perform material flow planning automatically from provisioning the required input data to the output of the optimization scenarios. System breaks are to be avoided to enable automated and continuous planning.

- The data basis for the decision support system should be collected as far as possible using sensors. This should create the necessary real-time reference and achieve independence from historical company data. Constraints will serve as additional data input if the needed data cannot be captured by sensors (planned production growth per year, etc.).

- The layout design, the material flow, the resource deployment of personnel and technology, and the examination of automation potentials are to be optimized. This is intended to create holistic planning of internal transport systems. Seasonality and growth scenarios are also to be integrated into the optimization procedure.

- The optimization steps should use operations research methods. Linear programming and heuristics will be used to identify weaknesses and calculate optimization scenarios. MCDM shall be used to weigh the constraints.

In addition to the requirements, limitations occur: Material flow systems consist of the components transport unit, transport technology, and transport organization (Martin 2016). The decision support system is intended to optimize the transport organization and to select the optimal transport technology. Optimization of the transport unit should not be executed. Load carriers with the dimensions of a euro pallet are assumed. The load factor of the forklift is defined with one pallet per transport for the current as well as for the optimized state. In addition, the transport technology is restricted to manual and automated forklifts. Only sensor data from manual forklifts will be used as data input. The area of application is to be limited to manufacturing companies. Material flows between goods receipt to production and production to goods issue shall be optimized. The storage technology used is a constraint considered, but it will not be optimized.

3.2. Conceptual Design of the Decision Support System

To achieve the objectives of this paper, a concept for an automated, sensor-based decision support system is developed that serves as a reference architecture. The structure of this conceptual decision support system is shown in Figure 1 and inspired by the structure of decision support systems described by Ben Rabia and Bellabdaoui (2022). It consists of three layers, which are discussed below.

- The data layer represents the interface to the input data. Sensor data is imported into the decision support system during the data collection function. In addition, the planning team defines constraints, which are also embedded in the system. The data processing function checks, prepares, and processes the collected sensor data. In the final step, the resulting data is stored in a database, which acts as an interface to the model layer.

- The analysis, calculation, and optimization logic are integrated into the model layer. Operations research methods are used to perform the functions assessment of constraints, weakness analysis, forecast, and optimization. The results of the model layer are identified weaknesses in the material flow and calculated optimization scenarios of the actual and target state under consideration of the defined constraints.

- The knowledge layer is used for supporting data-driven and efficient decision-making by the planning team. For this purpose, the solution evaluation assesses the planning results of the model layer qualitatively and quantitatively. The visualization graphically prepares all necessary information for the planning team. The report function documents the identified weaknesses and the calculated recommendations for material flow optimization.

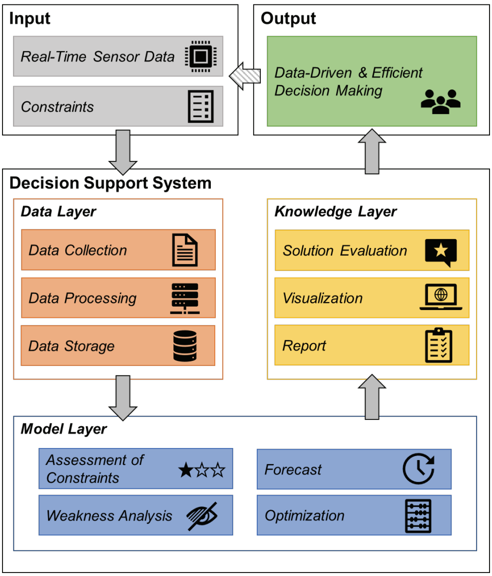

Figure 1: Concept of the decision support system

3.3. Data Layer

A holistic and up-to-date database is crucial for successful decisions in material flow planning. The collection, processing, and storage of this database is the task of the data layer. For this purpose, sensor data are defined that must be determined

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during data collection. Table 1 shows mandatory sensor data, relevant measured values, and required data type. Depending on the application, the table can be extended by further optional sensor data. For example, the ambient temperature in refrigerated warehouses may be of interest.

Real-Time Sensor Data	**Relevant Value**	**Data Type**
Timestamp	Time of reaching source/sink	DateTime
Travel time	Time interval in seconds between leaving the source and arriving at the sink	Integer
Handling time	Time interval in seconds between entering the source/sink and leaving the source/sink	Integer
Source	Starting point of the transport	String
Sink	End point of the transport	String
Route	Passed points and intermediate stops	String
Distance	Distance in meters of the traveled transport route	Integer
Loading condition	Loading condition of the forklift	Boolean
Lifting height	Maximum lifting height in meters performed during the transport	Integer
Transported weight	Maximum lifted weight in kg performed during the transport	Integer
Forklift vibrations	Maximum vibrations to which the forklift has been subjected	Integer

Table 1: Mandatory sensor data

Constraints are needed to guarantee realistic planning of the decision support system and must be defined by the planning team. On the one hand, these link the sensor data and the real world. A list of the currently used forklifts is used to assign the sensor ID to the means of transport. In addition, the type and the currently assigned function area must be defined. The position of the sources and sinks in the layout and their assignment to the sensor data must also be recorded by a list. Information on the space requirements, the use of the areas (production or warehouse), the material group concerned, and the type of transfer point (e. g. rack, conveyor system) must be defined. Information on the transport paths, such as width, gradient, indoor or outdoor use, and any mixed traffic must be provided.

On the other hand, data must be collected if it cannot be recorded using sensors. This includes data such as current shift schedules, secondary activities performed by forklift drivers, and the planned production volume growth in a defined planning horizon. In addition, a correction factor for seasonality should be specified if the sensor data was only collected temporarily. The constraints are concluded with a technology database that, according to VDI 2198 (2019), contains the core characteristics of current forklifts and automated guided vehicles. This database should be updated annually and not anew for each application. Microsoft Excel lists are provided for all these defined constraints, which can be automatically inserted into the decision support system. Figure 2 summarizes the required constraints. Mandatory constraints that must be fulfilled are indicated (M).

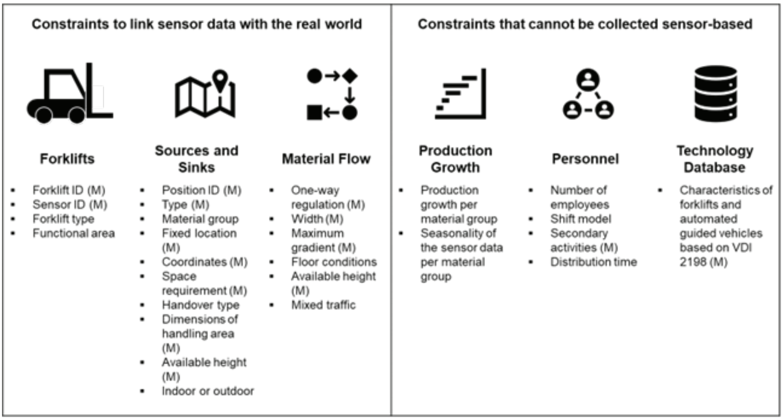

Figure 2: Required constraints of the DSS for material flow planning

After data collection, data processing takes place. First, the sensor data is checked for completeness and consistency. Incorrect sensor data are cleaned, duplicates are removed, and missing data records are added. Individual data records are combined to form integrated database entries. For this purpose, missing mandatory sensor data are calculated using other recorded data and defined formulas. For example, if the handling time is not recorded sensor-based, it can be determined by subtracting two consecutive time stamps and the measured travel time. If cal-

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culations are not possible, the planning team is informed that additional constraints are needed. For example, if the lifting height cannot be measured using sensors, the maximum lifting height required for each source and sink must be specified as an additional constraint.

Finally, the prepared data are stored in a database. It consists of the tables sensor-based material flow data, planning constraints, and technology database. These tables are the starting point for optimizing material flows in the model layer.

3.4. Model Layer

The model layer contains the optimization logic of the material flow planning and applies operations research methods during the functions assessment of constraints, weakness analysis, optimization, and forecast. Figure 3 shows, as an introduction, the optimization procedures, their results as well as the information flows between these procedures.

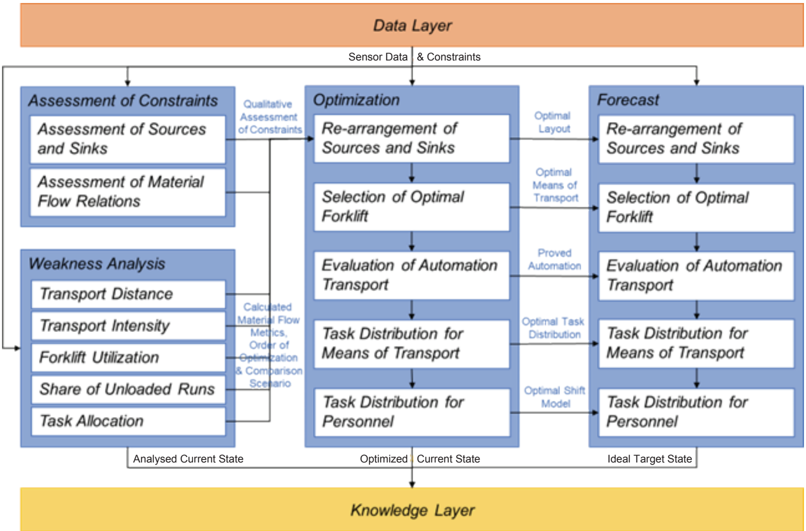

Figure 3: Structure of the model layer

First, the assessment of constraints function evaluates the optimal positions of sources and sinks and the quality of material flows using MCDM. The results are used to incorporate qualitative criteria into material flow planning during the optimization function. Both assessment procedures are described in the following.

The sources and sinks are evaluated using a pairwise comparison. Each position is seen as an alternative to every other position. Iteratively, the constraints of the original position are compared with the alternative position to be evaluated. Nine constraints for sources and sinks are used (see Figure 2, column 2). The following evaluation scheme occurs: If mandatory constraints are not fulfilled by the alternative position or less than four of the nine constraints are met, zero points are given. Zero points are also assigned if the source has the property fixed location. For example, a production line cannot be relocated. Therefore, all other positions in the layout are not suitable. If a maximum of six constraints are fulfilled, one point is awarded. Two points mean that a maximum of eight constraints are met. In the case that all constraints are fulfilled, three points are given. Four points are awarded if all constraints are met and at least one constraint is over-fulfilled compared to the original position, (e. g. an alternative has a more generous transfer area than the original position). The best score is five points if all constraints are met and at least three criteria are exceeded. After all, combinations have been evaluated, the results are documented in an evaluation matrix.

In the second step, the qualitative assessment of the material flow relations between the sources and sinks is done. For this purpose, the defined material flow constraints track width, maximum gradient, floor conditions, available height, and mixed traffic are evaluated. The actual constraints per transport relation are compared with the ideal condition using a pairwise comparison. The ideal transport route width is calculated based on the number of travel lanes incl. safety distances. In the optimal case, no gradients occur. The ideal ground conditions are without obstructions or damages, and suitable for automation according to VDI 2510 Part 1 (2009). Gates are usually limiting transport routes. In ideal conditions, there are no height limitations along the transport route. Ideally, there is no use of various transport vehicles or flows of people in the same area. In an iterative process, all occurring material flow relations are evaluated. The material flow relation receives one point for each criterion fulfilled. A maximum of five points per relation can be achieved. The results are documented in an evaluation table.

In addition, the weakness analysis function is used to analyze the actual situation of the material flow system based on the generated sensor data. This identifies the effort drivers that are to be eliminated during optimization. This is done by calculating material flow metrics such as traveled transport distances and intensities, forklift utilization, the share of unloaded runs, and task allocation per means of transport, per shift, and per hour based on the sensor data. The calculated key figures and the evaluated actual situation serve as a calculation basis for quantifying the optimization potential. Furthermore, the order in the optimization function is determined based on the weakness analysis. Critical challenges with high optimization leverage are optimized first, and non-critical conditions last.

The optimization function is based on the assessment of constraints and the calculated material flow metrics of the weakness analysis. The optimization procedure starts with re-arranging sources and sinks to minimize the transport intensities using a heuristic greedy algorithm.

First, the algorithm places those sources and sinks with a fixed location assessment. The remaining sources and sinks are located to minimize the transport intensities. The number of actual outgoing material flows per position defines the order of this iteration process. The source/sink with the highest total transport load is placed first and the one with the lowest last. The algorithm places the source/sink on the alternative positions in the layout based on the evaluated suitability of the alternatives, which must have a rating of at least one point. The alternative positions with a high rating are prioritized, and positions with a low rating are avoided. The source/sink is rearranged until the cumulated transport intensities of all material flows arising so far result in a minimum. If several transport routes can be made, the qualitative evaluation of the material flows is considered. This is done if the difference in the transport distances of the variants deviates by a maximum of ten percent. In addition, the load on the transport network is calculated for each sub-route and considered in the selection of transport routes. The risk of bottlenecks and congestion is avoided by distributing the transport loads over different sub-routes although this can result in longer transport routes. If the position of the source/sink and the transport route is defined, the positioning of the next source/sink is continued. After all sources and sinks have been placed, the final calculation of the transport intensities of the optimized material flow is performed.

Once the transport intensities have been minimized, the optimal means of transport are selected for each task. A pairwise comparison is performed by comparing the properties of forklifts of the technology database with the constraints of the optimized layout. A forklift is considered suitable if it meets all mandatory constraints. Since various vehicle types can occur, the number of vehicles is limited to those that can be used in all or at least in most tasks in a second iteration step. This creates maximum flexibility and reduces the number of vehicle types.

In the next optimization step, the automation of the selected forklifts is evaluated. For this purpose, automated guided vehicles (AGV) are chosen if they correspond to the constraints of the re-arranged layout and the defined material flows. These constraints are evaluated in a pairwise comparison with the properties of the automated guided vehicles of the technology database. If all mandatory and optional constraints are fulfilled, a suitable AGV type is selected. During this evaluation, the mixed traffic, floor conditions, and outdoor use are of greater importance than in selecting forklifts since these constraints strongly limit AGV use.

In the following optimization step, the transport tasks of the material flows are distributed to the selected transport systems to determine the optimal number of vehicles. This is done by assigning transport orders to forklifts in the sequence of the sensor-based detected time stamps using a greedy algorithm. The duration of the transport order is calculated by the sensor-based collected handling and driving times. If the forklift type is changed compared to the currently used forklift, a correction factor is considered to account for the different characteristics. Furthermore, the defined distribution times are integrated. When placing transport orders, an iterative approach is taken in two phases. In the first phase, the current function assignment of the forklifts is considered in the task allocation. In the second phase, no function allocation is considered. This should minimize the share of empty runs. In both phases, forklifts are chosen if their characteristics correspond to the transport order based on the selection procedure performed. For the following transport orders, an additional forklift is needed if the already chosen forklifts are already executing transport orders or do not meet the order specifications. This is done until all transport orders have been assigned to forklifts. Afterward, the utilization of each forklift is analyzed. For forklifts with low utilization rates below 50 percent, an attempt is made to transfer the transport load to other forklifts of the same type. This is done by slightly varying the time stamps and the defined distribution time. After both phases (with and without functional area assignment) have been executed, the results are compared. The phase with the lower number of means of transport is used for optimizing personnel deployment.

To distribute workloads among personnel in a socially even and balanced manner, an optimized shift schedule for forklift drivers is created. For this purpose, the forklifts are grouped so that the shifts can be optimally staffed. Each group is assigned to an employee who executes the orders of the assigned forklift pool. In the first step, planning is done with predefined shift models. In the second step, an ideal creation of a new shift model takes place. In both cases, the task allocation considers required secondary activities. Finally, the required employee capacities per phase are compared to determine the optimal variant.

The forecast function integrates the targeted company growth in a defined planning horizon into the optimization procedure. In addition, the generated sensor data is adjusted for seasonal fluctuations, for example, to avoid variations due to the limited availability of sensor data. Transport orders are automatically generated and added to the sensor-based collected database to account for growth and seasonality. This supplemented data includes the addition of production lines or the acceleration of the production cycles of the current production lines depending on the given constraints. Through these additional data sets, the target state is achieved, which is optimized using the described methods of the optimization function.

The results of the model layer, the analyzed weaknesses of the actual state, and the optimized actual and target state are finally transferred to the knowledge layer.

3.5. Knowledge Layer

The knowledge layer is developed for knowledge transfer to the planning team. First, the scenarios calculated by the model layer are evaluated in the solution evaluation function regarding their technical feasibility. This is done by checking if the defined constraints are met. In addition, optimization potentials are to be evaluated quantitatively. For this purpose, the savings of transport intensity, resource usage,

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time, and cost savings are calculated compared to the actual situation. A sensitivity analysis is done to consider the influence of the selected methods and constraints on the results. The results of the solution evaluation and those of the model layer are graphically prepared for the planning team using the visualization function. This includes the visualization of the calculated layout variants, sankey diagrams, distance-intensity matrices, and shift plans for the current state, the optimized current state, and the optimally designed target state. The report function serves as a written summary of the planning results. It contains a chronological list of recommended actions to achieve the optimal target state for each planning step.

All these reports and diagrams are provided for the planning team. Complex planning problems are presented. Thus contribute to an efficient and data-driven decision-making process for optimizing internal material flows. The analyzed actual state shows the planning team the weaknesses of the current material flow system. The optimized actual state supports achieving short-term efficiency improvements. The result of the optimized target state provides recommendations for action to handle the planned company growth in intralogistics. If alternative scenarios are still to be considered, the data input of the constraints can be revised, and the automated planning of the decision support system can be started again. In addition, further sensor data can be integrated into the model to expand and optimize the planning results. This process can be iterated until all relevant scenarios have been examined, and an optimal decision can be made.

3.6. Discussion of results

During this section, a decision support system for internal material flow planning was designed. This system combines operations research methods to create a holistic planning and optimization of material flows executed by forklifts. Compared to related works in section 2, which deal with one-dimensional planning problems, multidimensional challenges of material flow planning (source/sink arrangements, deployment of resources/personnel, and automation potentials) can be solved.

The need for using sensors and their real-time data basis is highlighted in related works as an urgent need for research. Estanjini et al. (2010) provided a decision support system based purely on sensor data for optimizing the use of forklifts. Combined with the previously discussed multidimensional solution approach, a significant contribution to the state-of-the-art could be made during this contribution. The real-time reference of this conceptual decision support system improves the optimization results of standard operations research methods. In addition, it prepares decision-making efficiently and based on actual data. To ensure sufficient quality of the sensor data, supporting procedures for the selection and use of optimally suited sensors should be considered in future works.

The modular structure and the designed algorithms of the conceptual decision support system enable the automation of the planning steps of material flow concept planning from data collection to the preparation of recommended actions.

This creates an increase in efficiency and a reduction in planning times compared to the state of the art. The manual collection of the needed constraints is still an exception. Future research should focus on automating the determination of planning constraints (e. g. automated identification of track widths from plant layouts). In summary, it can be stated that the conceptually designed, sensor-based decision support system exceeds the state-of-the-art and fulfills all requirements defined in section 3.1.

3.7. Discussion of challenges of the transfer to public transport

This contribution aims to transfer the conceived, internal decision support system to public transport. In advance, potential challenges that prevent a transfer will be discussed before the concept is transferred in section 4. As in intralogistics, public transport is a material flow problem to get the right object to the right place at the right time in the right quantity and quality at minimum cost. Therefore, a transfer of intra-logistics concepts to public transport can be concluded. Due to some possible differences in specific use cases, challenges may arise that prevent a transfer. The conceptually designed decision support system is limited to internal forklift transports. During public transport, analogies to milk run systems in the industry, which are generally not implemented using forklifts, occur in the case of bus or tram transports. The fundamentally different logic of milk runs could cause limitations during transfer. The application area in section 4 is the implementation and evaluation of crowdsourcing delivery using tramways in Vienna to create sustainable, intra-city parcel delivery on the last mile. The focus of the conceptual decision support system is techno-centric and economic. The consideration of sustainability criteria is currently not considered. This lack of sustainability aspects can also make transfer difficult. Finally, the data basis and structure are designed for using sensors on internal forklifts. Other sensors will be used in public transport. In addition, different sensor data will serve as data basis. Needed adjustments to this new data structure can also prevent a transfer. In public transport, significantly higher requirements are to be assumed regarding data security, handling of personal data, and legal aspects. Restrictions can also arise due to these factors.

4. Transfer to Public Transport

Challenges arise not only in the internal but also in the external material flow due to shorter delivery times and increasing e-commerce. In particular, the sustainable and efficient delivery of parcels on the last mile is currently not possible. Crowdsourcing delivery is seen as a solution to this challenge. The concept of crowdsourcing delivery implies the delivery of parcels by a network of individuals who deliver them along their routes using underutilized resources (Ciobotaru/Chankov 2021). Data-driven research on the transport routes of passengers, means of transport, and goods to quantify the potential of crowdsourcing delivery in public transport has not yet been done.

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Due to the resulting lack of data-based decision-making, this is one of the reasons why crowdsourcing delivery has not yet become established (Le et al. 2021; Yildriz 2021).

The Öffi-Packerl research project is currently addressing this research gap. This project aims to use unused transport capacities of Viennese tramways for parcel deliveries on the last mile. This shall be achieved by the concept of crowdsourcing delivery, where passengers act as transporters of parcels. Therefore, prototypes of a mobile smartphone app that serves as a transport management platform and associated, autonomous parcel stations at tramway stops are to be developed. Figure 4 shows the concept of the Öffi-Packerl project based on these prototypes.

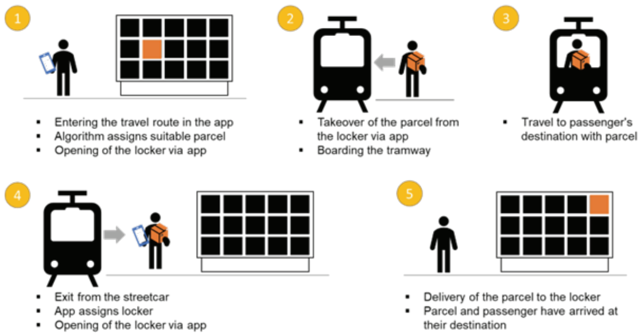

Figure 4: Concept of the Öffi-Packerl research project

By implementing these prototypes, data will be collected for the first time to quantify the potential of crowdsourcing delivery in public transport. This will serve as a basis for decision-making on implementing this concept in Vienna. For example, the decision-making process includes the stops suitable for parcel stations due to space restrictions or relevant tramway lines regarding passenger numbers. For this purpose, Figure 5 shows to what extent the decision support system can be transferred to the Öffi-Packerl project.

The data layer can be transferred almost unchanged to the Öffi-Packerl project. The sensor data will mainly be GPS data, for example, to evaluate the duration of transfers with pickup or placement of a parcel. In addition to the sensor data, app data will occur in real time. These must be additionally integrated into the data processing and storage. Since personal data is recorded using the app, higher data protection guidelines come into force as a supplement. Secure encryption of the data must be ensured. The assessment of constraints function can be applied unchanged to public transport. The assessment of sources and sinks in intralogistics is used for assessing public transport stops. The assessment of material flow relations corresponds to the assessment of tramway lines. The weakness analysis still calculates the required transport metrics, but the analysis for weaknesses is not required. The other functions of the model layer need to be adapted. The algorithms for task distribution of forklifts and personnel of the optimization function can be seen as a basis for the matching algorithm of passengers, parcels, and tramways. However, a specific further development to the concrete challenges of Öffi-Packerl is necessary. The optimization of the transport routes of the packages in the public transport network can be done based on the algorithm for layout optimization. The selection of suitable manual and automated transport systems is not considered relevant for the Öffi-Packerl project. The forecast function shall continue to optimize target states. This is done based on the adapted algorithms of the optimization function. The tasks of the knowledge layer functions remain unchanged compared to intralogistics. Only the creation of higher data security must also be considered.

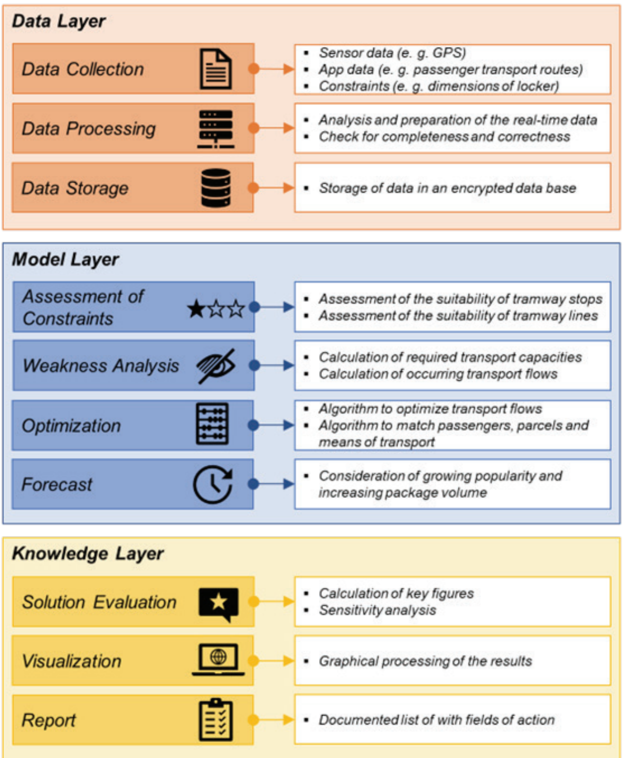

Figure 5: Transfer to crowdsourcing delivery in public transport

In summary, it can be stated that the developed internal decision support system can significantly contribute to the Öffi-Packerl research project. The transferability to public transport and in particular to crowdsourcing delivery is shown. This demonstrated that in-plant methods such as operations research can contribute to sustainability outside of industrial use cases. The expected challenges in section 3.7 that might prevent transfer can thus be disproved, although significant adjustments must be made, especially in the model layer and its algorithms.

5. Conclusions

In this contribution, a decision support system has been conceptually designed. This system enables holistic, realistic, data-driven, and efficient material flow planning of internal transport systems based on operations research methods. The data basis is collected by sensors and required constraints are defined. The structure of the decision support system consists of three layers: data, model, and knowledge layer. The data layer collects, prepares, and stores the required database. The model layer integrates logic and algorithms to analyze, evaluate and optimize material flows, source and sink arrangements, deployment of resources and personnel, and automation potentials of forklifts. The knowledge layer prepares the planning results in an easily understandable way and thus enables efficient and data-driven decisions by the planning team. This decision support system exceeds the state-of-the-art due to the consideration of multidimensional planning problems of internal transport, the real-time reference through the integration of sensor data, and the automation of material flow concept planning from data collection to the derivation of recommended actions.

Since similar challenges arise in the application of crowdsourcing delivery, the transferability of the developed concept to public transport was evaluated in the Öffi-Packerl research project. It was demonstrated that the discussed decision support system can be transferred to public transport. For this purpose, the model layer and its algorithms must be adapted. The data and knowledge layer can be transferred almost unchanged. This paper shows that expected challenges that prevent a transfer could be disproved and industrial management methods can contribute to a sustainable future outside of factories.

Further research concerns the selection of suitable sensors and the integration of these into the decision support system. In addition, sustainability criteria will be integrated into decision support for material flow planning. Furthermore, the concept should be transferred into a software demonstrator for decision support in material flow planning. This demonstrator should be applied in case studies at manufacturing companies in different industries to quantify the added value compared to conventional methods of material flow planning.

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References

Amulu Priya, S., Maheswari, V., Balaji, V. (2021). Operations Research for Supply chain management – An Overview of Issue and Contributions. In: J. Phys.: Conf. Ser. 1964 (2). 22010.

Ben Rabia, M., Bellabdaoui, A. (2022). Simulation-based analytics: A systematic literature review. In: Simulation Modelling Practice and Theory 117. 102511.

Berndt, M., Fischer, C., Krummacker, D., Schotten, H. (2021). Deterministic Planning for Flexible Intralogistics. In: Chenguang Yang (Hg.): System intelligence through automation & computing. 2021 the 26th International Conference on Automation & Computing. p. 1–6.

Burggräf, P., Adlon, T., Hahn, V., Schulz-Isenbeck, T. (2021). Fields of action towards automated facility layout design and optimization in factory planning – A systematic literature review. In: CIRP Journal of Manufacturing Science and Technology 35. p. 864–871.

Carli, R., Dotoli, M., Digiesi, S., Facchini, F., Mossa, G. (2020). Sustainable Scheduling of Material Handling Activities in Labor-Intensive Warehouses: A Decision and Control Model. In: Sustainability 12 (8). 3111.

Chakraborty, S., Saha, A. (2022). Selection of Forklift Unit for Transport Handling Using Integrated MCMD under Neutrosophic environment. In: Facta Universitatis. Series: Mechanical Engineering. p. 1–23.

Ciobotaru, G., Chankov, S. (2021). Towards a taxonomy of crowdsourced delivery business models. In: Int. Journal of Physical Distribution and Logistics Management 51 (5). p. 460–485.

Coelho, F., Relvas, S., Barbosa-Póvoa, A. (2021). A simulation-based decision support tool for in-house logistics: the basis for a digital twin. In: Computers & Industrial Engineering 153. 107094.

Dickmann, P. (2015). Schlanker Materialfluss. Mit Lean Production, Kanban und Innovationen (3. Auflage). Berlin, Heidelberg: Springer Vieweg.

Ecker, C.; Riester, M.; Schlund, S. (2023). Duck Box: Sensor-Based Material Flow Optimization for Economically and Energy-Efficient Intralogistics. In Proceedings of the 12th International Conference on Smart Cities and Green ICT Systems, ISBN 978-989-758-651-4, S. 113–120.

Estanjini, R., Lin, Y., Li, K., Guo, D., Paschalidis, I. (2011). Optimizing Warehouse Forklift Dispatching Using a Sensor Network and Stochastic Learning. In: IEEE Trans. Ind. Inf. 7 (3). p. 476–486.

Fazlollahtabar, H., Smailbašić, A., Stević, Ž. (2019). FUCOM method in group decision-making: Selection of forklift in a warehouse. In: Decis. Mak. Appl. Manag. Eng. 2 (1). p. 49–65.

Hayward, S.J., van Lopik, K., Hinde, C., West, A.A. (2022). A Survey of Indoor Location Technologies. Techniques and Applications in Industry. In: Internet of Things 22. 100608.

Hosseini-Nasab, H., Fereidouni, S., Fatemi Ghomi, S., Fakhrzad, M. (2018). Classification of facility layout problems: a review study. In: International Journal of Adv. Manufacturing Technology 94. p. 957–977.

Kibira, D., Hatim, Q., Kumara, S., Shao, G. (2015). Integrating Data Analytics and Simulation Methods to Support Manufacturing Decision Making. In: Proceedings of the 2015 Winter Simulation Conference. p. 2100–2111.

Kluska, K. (2021): Support the Decision Processes in Management Through the Automatic Generation of Simulation Models of Warehouses. In: European Research Studies Journal Vol. 24(5). p. 379–398.

Korth, B., Schwede, C., Zajac, M. (2018). Simulation-ready digital twin for real-time management of logistics systems. In: 2018 IEEE International Conference on Big Data Proceedings. p. 4194-4201.

Le, T.V., Ukkusuri, S.V., Xue, J., van Woensel, T. (2021). Designing pricing and compensation schemes by integrating matching and routing models for crowd-shipping systems. In: Transportation Research Part E: Logistics and Transportation Review 149. 102209.

Mahmutagić, E., Stević, Ž., Nunić, Z., Chatterjee, P., Tanackov, I. (2021). An Integrated Decision-Making Model for Efficiency Analysis of the Forklifts in Warehousing Systems. In: FU Mech Eng 19 (3). 537.

Marinkovic, M., Galka, S., Meißner, S. (2023). Digital Twins for Internal Transport Systems: Use Cases, Functions, and System Architecture. In: Proceedings of the 56th Annual Hawaii International Conference on System Sciences. p. 1195–1205.

Martin, H. (2016). Transport- und Lagerlogistik, Systematik, Planung, Einsatz und Wirtschaftlichkeit (10. Auflage). Wiesbaden: Springer Vieweg.

Müller, M., Reggelin, T., Schmidt, S. (2018). Operational Simulation-Based Decision Support in Intralogistics using Short-Term Forecasts. p. 1–8.

Pamučar, D., Ćirović, G. (2015). The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation Area Comparison (MABAC). In: Expert Systems with Applications 42 (6). p. 3016–3028.

Pfohl, H.-C. (2023). Logistics Management. Conception and Functions. 1st ed. 2023. Berlin, Heidelberg: Springer Berlin Heidelberg.

Rahnamay Bonab, S., Jafarzadeh Ghoushchi, S., Deveci, M., Haseli, G. (2023). Logistic autonomous vehicles assessment using decision support model under spherical fuzzy set integrated Choquet Integral approach. In: Expert Systems with Applications 214. 119205.

VDI 2198 (2019). Type sheets for industrial trucks. p. 1-28.

VDI 2498 Part 1 (2011). Procedure in material flow planning. Fundamentals. p. 1-15.

VDI 2510 Part 1 (2009). Infrastructure and peripheral installations for Automated Guided Vehicle Systems (AGVS). p.1–22.

VDI 2689 (2019). Manual of material flow investigations. p. 1–40.

Yazdani, M., Zarate, P., Coulibaly, A., Zavadskas, E. (2017). A group decision-making support system in logistics and supply chain management. In: Expert Systems with Applications 88, p. 376–392.

Yazıcı, E., Alakaş, H., Eren, T. (2022). Analysis of operations research methods for decision problems in the industrial symbiosis: a literature review. In: Environmental science and pollution research international 29 (47). p. 70658-70673.

Yildriz, B. (2021). Express package routing problem with occasional couriers. In: Transportation Research Part C: Emerging Technologies 123. 102994.

DOI: https://doi.org/10.30844/wgab_2023_2

Zubair, M., Maqsood, S., Omair, M., Noor, I. (2019). Optimization of Material Handling System through Material Handling Equipment Selection. In: International Journal of Progressive Sciences and Technologies (IJPSAT) Vol. 15(2). p. 235–243.