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Integrating Smart Production Logistics with Network Diagrams: A Framework for Data Visualization

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Abstract. This paper introduces a framework that integrates smart production logistics (SPL) with network diagrams. This integration enhances visibility in the material and information flow within the manufacturing sector, thereby adding value through data visualization. Drawing from a detailed case study in the automotive industry, we outline the essential components of network diagrams that are tailored to depict spatial-temporal data linked with material handling processes in an SPL context. This integrated approach presents managers with a new tool for optimizing planning and executing tasks related to the transport of materials and information. Furthermore, while the framework brings about significant technological progress, it also emphasizes the managerial implications of SPL data visualization. In particular, it highlights its potential to foster informed decision-making, resource optimization, and strategic forecasting. The paper also discusses prospective research avenues, stressing the importance of dynamic diagrams that decode complex patterns from digital data and the incorporation of sustainability metrics in SPL assessments.

Keywords. Smart production logistics, Network diagram, Data visualization, Automotive industry, Case study

1. Introduction

Recent research underscores the critical role of digital technologies in enhancing the visibility of materials [1] and information within manufacturing processes, a cornerstone for improvements in productivity, delivery, and overall revenue. Within this technological paradigm, Smart Production Logistics (SPL) emerges as a key domain, leveraging the industrial Internet of Things (IIoT), cyber-physical systems (CPS), and big data analytics to foster dynamic perception, responsive actions, and autonomous decisions in production logistics. The primary ambition of SPL is to augment visibility, control, adaptabil-

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ity, and predictive capabilities concerning material and information movement within the confines of manufacturing environments.

The deployment of digital technologies in SPL significantly bolsters connectivity, facilitates real-time data collection, streamlines data management and analysis, and underpins data-driven decision-making. A pivotal element in harnessing the full potential of SPL is the intricate understanding of the interplay among various resources, including personnel, forklifts, automated guided vehicles (AGVs), and autonomous mobile robots (AMRs), all of which are integral to efficient material transportation within factories.

Despite significant strides in digital technology adoption within SPL, a gap remains in the literature concerning the effective visualization of the complex data landscapes generated in such environments. While current research emphasizes information acquisition, handling, and task automation, there exists a burgeoning need to equip decision-makers with structured, intuitive tools that unveil hidden patterns and enhance visibility in material and information flows. Network diagrams, characterized by their ability to depict relationships between entities through nodes and connecting arcs, present a promising avenue to address this need. However, their application in SPL contexts remains underexplored, representing a missed opportunity to leverage their potential in supply chain and social network analysis.

In response to this gap, this paper proposes a novel framework that integrates SPL with data visualization through network diagrams, aiming to enhance the visibility of material and information flow in manufacturing material handling. Drawing upon empirical data from a case study conducted at an automotive manufacturing facility, this research endeavors to make two primary contributions: first, a detailed characterization of network diagram components tailored for visualizing spatial-temporal data related to material handling in manufacturing; and second, the provision of valuable insights for managers tasked with overseeing the planning and implementation of material and information movement tasks.

The remainder of this study is organized as follows: Section 2 delves into related studies to lay the groundwork for our research. Section 3 outlines the methodological approach adopted for our case study, detailing data collection and analysis procedures. Section 4 presents the empirical findings, and Section 5 discusses the implications of these findings, both theoretically and practically. Finally, Section 6 concludes the study by summarizing the key contributions and suggesting avenues for future research.

2. Related studies

2.1. Smart production logistics

SPL utilizes digital technologies in physical factories to analyze network-wide material, parts, and product flows in the complete value-added chain [2]. An essential requirement for achieving SPL is the development of digital capabilities that enable manufacturing to acquire, handle, and utilize information to increase visibility [3]. The literature highlights specific digital technologies required for these capabilities [4, 5].

Information generation for real-time material identification relies on technologies such as IIoT devices, radio frequency identification (RFID), sensors, cameras, and CPS [6, 7, 8]. These technologies are vital for cross-platform information sharing and enhancing visibility, a requisite for planning spatially and temporally distributed complex systems [4].

Handling information includes the ability to store and process data (e.g., volume, variety, velocity, veracity, and value) with the purpose of achieving critical insights into the movement of materials and information [9]. In relation to increasing visibility, the literature associates the technologies of IIoT, big data analytics, cloud computing, and mobile systems to this capability [1]. These technologies increase visibility because they help analyze data and establish linkages across data sets from various sources that help improve the visibility of stock levels or lead times [10].

Information use entails applying digital technologies to enhance predictive capabilities, automate tasks, and support staff decision-making [3]. Digital technologies linked to information use encompass big data analytics, artificial intelligence, digital twins, and CPS [4]. The importance of the information use capability lies in its capacity to improve visibility by enabling predictive actions to prevent disruptions in material and information flow.

Despite the advancements in digital technology applications within SPL, the literature indicates a gap in tools that provide intuitive access to processed data for decision-makers, underlining a need for enhanced data visualization techniques in SPL.

2.2. *Network diagrams for material handling*

Smart manufacturing has catalyzed a transformation in the perception and handling of manufacturing data. One key element of this shift is the integration of real-time data with data visualization techniques. These techniques not only render the processed data more comprehensible but also promote an interactive environment. Tools, ranging from diagrams and graphs to immersive virtual reality, serve as the backbone of this visualization process [11].

Within the domain of production logistics, the approach to data visualization is both vast and detailed. Techniques such as heat maps, time-series zone frequency graphs, and time-based trajectory maps provide essential insights. These methodologies bridge the communication gap, offering a language that is universally understandable to stakeholders, from on-ground logistics operators to top-tier managers [12]. However, while trajectory information sheds light on certain logistics facets, it doesn't capture the full picture. Deeper layers of data and their implications await exploration.

The introduction of technologies like RFID has accelerated the data influx in production logistics. While this influx is invaluable, it can also become overwhelming. Big data analytical tools emerge as pivotal assets for deriving meaningful insights. By employing machine learning techniques, patterns can be identified and actionable conclusions drawn [13].

Visualization of intricate logistics data transcends mere clarity; it converts raw data into decisive insights that influence decision-making. Through this data dissection, logistics trends emerge, operator performances stand evaluated, and granular insights become attainable [14].

Beyond production logistics, urban logistics and transportation have also been transformed by data visualization. A notable advancement in this realm is the conceptualization of multivariate trajectory data, interpreting attributes based on both geographical and abstract space [15]. Graph models and network diagrams offer a sweeping perspective of urban transportation dynamics. Innovative techniques, like the graph partitioning algorithm, enable the transformation of detailed street-level data, such as that from taxis, into more digestible region-level graphs [16].

The maritime sector, awash with Automatic Identification System (AIS) data, follows a similar trajectory. For stakeholders lacking expertise in data mining, visual depictions of this data are crucial. These visual tools facilitate real-time monitoring, aid in understanding vessel behaviour, and bolster navigation safety, particularly in congested maritime regions [17].

In conclusion, whether examining urban expanses or delving into traffic analysis, one constant remains: the unparalleled importance of network diagrams and visualization techniques. These tools clarify people's flow within cities, layout infrastructural blueprints, and guide trajectory pattern mining endeavors [18, 19]. Progressively, innovations such as spatio-temporal trajectory clustering enhance the comprehension of transportation networks and their multifaceted dynamics [20].

However, the current literature suggests that the full potential of network diagrams in visualizing the intricate logistics data within SPL contexts is yet to be fully realized. This underutilization points to a significant research opportunity, particularly for enhancing the visibility and management of material and information flows in manufacturing environments.

2.3. Spatio-temporal data visualization with network diagram

A network diagram is a visual representation that displays the relationships between entities. These entities are usually represented by circles (referred to as nodes) and are connected by lines to illustrate the links among them [21]. Such diagrams are commonly used in areas like social network analysis [22], transportation, and logistics to understand the dynamics. The direction of a flow can be indicated using arrows and glyphs on the connecting lines. For clarity, it's important to incorporate legends, annotations, labels, and symbols to explain the color, opacity, node size, line width, shape, and other visual cues in the visualization. Here, size often indicates the magnitude of an entity, while line width can denote the strength of a flow or relationship. In a layered diagram, entities can be grouped into different tiers, and these layers can be employed to show groups of nodes.

Spatio-temporal visualization facilitates the comparison or aggregation of data across various time periods, allowing for the observation of changes over time. If the dataset includes geospatial data or coordinates, nodes can be mapped to their real-world locations. This type of visualization is designed to represent the evolution of a network structure over time and space, aiming to uncover hidden patterns [23]. To visualize the network's dynamics, the diagram can be animated with a timeline or time axis. Additionally, nodes and edges can be added or removed to show entities that join or leave the relationship at particular times.

Interactive features, on the other hand, empower users to engage with the data dynamically. These capabilities include filtering data by specific time frames using a time slider, brush-linking on dashboards, zooming in or out on chosen areas, and spotlighting particular events. Often, for various users like managers or operators, it is beneficial to combine the static structural details with the dynamic flow changes in a comprehensive dashboard view.

One of the notable benefits of a network diagram is its intuitiveness, making it a popular choice in various sectors. The distance between nodes is typically consistent, and the spatial proximity of nodes perceptually implies a grouping. Notably, tracing paths is simpler in a less complicated diagram compared to a more intricate one.

Nevertheless, a significant drawback is its issue with scalability. As the number of nodes multiplies, challenges like visual clutter, intersecting edges, and overlapping nodes can hamper readability. Tracing paths becomes increasingly complex, especially as the number of links per node rises.

While network diagrams offer intuitive and versatile visualization options, challenges related to scalability and complexity management persist, especially as the volume of data increases. Addressing these challenges is crucial for effectively applying network diagrams in SPL environments, where data complexity and volume can be particularly high.

3. Method

This study utilizes a case study method to fulfil its objective. This selection is grounded in the method's appropriateness for real-life research settings, its capability to furnish detailed descriptions of evolving phenomena, and its potential to uncover emerging circumstances during data collection [24]. We employ an inductive approach in our case study to contribute to the theory. Specifically, we prioritize empirical data and draw upon existing literature on SPL to impart a sense of generality to our study's findings [25].

The focus of this study is improving the visibility of materials and information within the physical boundaries of factories. A key characteristic of visibility is information that is accessible, accurate, timely, complete, and applicable for enhancing operational performance [26]. Accordingly, the unit of analysis is the information in material handling leading to the delivery of materials in the right place, time, quantity, and cost.

The study gathers empirical data from a multinational automotive manufacturer. While single case studies have limited generalizability, they enable researchers to delve into phenomena under study in greater detail [27]. The selection of this manufacturing company is justified by three key factors conducive to the successful adoption of digital technologies in SPL within manufacturing: large company size, resource availability (including well-defined departmental responsibilities in R&D, production, logistics, and IT departments), and established production development processes [28].

Data collection occurred from December 2020 to April 2021, utilizing both quantitative and qualitative methods. Quantitative data comprised time and location data sourced from signals emitted by Bluetooth-equipped radio frequency identifiers (RFID). Additionally, we obtained access to the ERP system containing material handling order information. Qualitative data encompassed company documents, interviews, and field notes from on-site visits, involving various company personnel, including managers, planners, forklift drivers, engineers, and logistics experts. The aim of the qualitative data was to understand the material handling process and its quantitative data.

Our data analysis involved an iterative comparison of collected data and existing literature [24]. We followed a four-step approach recommended by Miles et al. [29]. First, we selected and cleaned RFID data, removing errors, verifying accuracy with material handling staff, and storing it in a database. The second step was to identify relevant material handling elements for our case study, with input from staff and data from the database. These elements included machining stations, delivery routes, forklift direction, position, and movement. We determined material movement by consulting knowledgeable staff and created a geographical diagram of these elements. In the third step, we analyzed our data in comparison with the literature, focusing on data visualization and relevant SPL frameworks. Two potential frameworks emerged: a node-link diagram and a matrix diagram. We selected the node-link diagram for its accurate representation of material and information flow, geographical locations, and interconnections among factory stations. Finally, we summarized our findings and drew conclusions by comparing our empirical data to the literature in SPL and spatio-temporal data visualization.

4. Empirical results: Data set from SPL environment

The manufacturing company, a global leader in heavy vehicle production, employs 57,000 people and operates ten facilities across Europe, Asia, and South America. This study focuses on material handling within a facility that produces axles and transmission shafts. Material handling in this facility depends on three manually operated forklifts to transport parts through soft machining, hardening, and hard machining processes. These forklifts manage 80 distinct tasks related to material transportation across processes.

The manufacturing company faces challenges when performing material handling tasks. Currently, forklift drivers follow fixed routes at predetermined times during a shift. They rely on experience to locate supplies, parts, and finished products, a practice prone to errors and time-consuming. Management has identified that these practices result in delayed deliveries, extended makespan, and unnecessary forklift movements. Figure 1 presents the virtual environment of material handling at the manufacturing company.

Figure 1. Virtual environment of material handling at the case company

The data connection begins with IIoT devices, which include one RFID tag for each forklift operator and 25 sensor points collecting real-time information about the forklifts. The UWB tags offer an accuracy of 10 cm. Real-time information comprises speed, distance, geographical coordinates, vibration, and time. Additionally, digitally generated delivery zones record the forklift's arrival and departure at each delivery point.

Node-RED is chosen as the middleware due to its user-friendly visual programming and its ability to connect to various APIs, hardware, and online services. Node-RED captures and processes information by converting raw data from IIoT devices into data regarding the AGV's position. It does so by calling the API from the cloud server, containing data from the RFID sensor points, and retrieving a JSON object. Subsequently, it establishes and maps the parameters needed to determine the AGV's position, including time, AGV name, longitude, latitude, speed, and acceleration, from the JSON object.

The information originating from the IIoT devices is stored in a database a relational database management system. The first database defines the layout, including object coordinates, distances between objects, and routes. The second database lists the material handling tasks performed by the AGV, the third contains the schedule for these tasks, the fourth holds the optimal routes proposed by the control service for material handling tasks, and the fifth records the routes taken by the AGV during task execution. Figure 2 presents the IIoT-based data originating from the movement of materials.

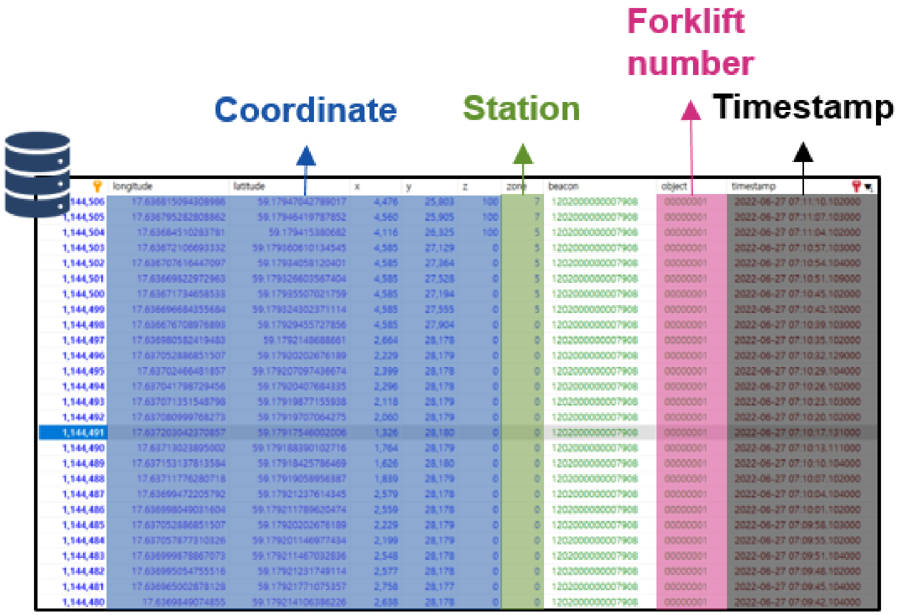

Figure 2. Data set originating from the movement of materials collected by IIoT devices

The virtual environment comprises a web-based application and a real-time location application. The web-based application displays real-time movement, traces previous positions, generates a forklift heat map, and identifies forklifts individually. The real-time location application uses real-time location information as an input and illustrates the forklift's position in 2D, along with highlighting the concentration of forklift activity.

5. Discussion

5.1. Integration and visualization of SPL data within network diagram

From our empirical findings, it is evident that SPL data embodies the characteristics of spatial-temporal data. However, standard network diagrams are insufficient for visualizing this type of data, primarily due to their inability to effectively represent the temporal dimension.

The goal of data visualization and infographics should always be to provide added value by offering diverse perspectives beyond simply presenting a dataset. This approach has gained traction across various business sectors, with sports analytics being a prime example. Within this domain, data visualization has been instrumental in extracting additional insights. In baseball, tools like the sabermetrics have been employed to determine player worth. However, the football industry faced challenges in data collection compared to baseball, given the continuous nature of the game and the complexities in quantifying in-game statistics. Thanks to advancements in computer vision technology, data accessibility in football has improved substantially. Consequently, data visualization techniques have grown increasingly popular within the sport. Interestingly, in the realm of production logistics, there has been limited exploration into which visualization elements are most effective.

To develop a framework that integrates a systematic matrix between network diagrams and SPL data, we catalogued components inherent to network diagrams. Our examination of existing literature revealed several key elements pertinent to these diagrams.

A network diagram can be conceptualized as a structure consisting of nodes and links, each possessing distinguishing attributes. Such diagrams can also be equipped with interactive features like filtering, brushing, linking, marking, and zooming. Given the spatial-temporal nature of SPL data, these interactive features are essential to accurately represent the dynamic nature of the data. Figure 3 presents a network diagram of material flow based on SPL data.

In visualizing SPL data, the three fundamental elements of a network diagram are aligned with SPL data components. Firstly, the position of each node signifies the location of pickup and delivery points within the SPL environment. While SPL data includes a time window, an aggregated network diagram can also be presented for initial data analysis. In such cases, the size of node could represent the duration spent at a specific pickup and delivery point by the material handling equipment. This representation allows users to discern which nodes accommodate more equipment at a given location. If the size of a node is disproportionately large compared to others, log scales or scale factors should be considered. The connection between nodes may be represented by bidirectional arrows, given the variance in routes. The thickness of the link can mirror the cumulative number of deliveries between two nodes. Attributes like labels, colors, and icons can be tailored to user requirements.

As for interactivity, it is vital that users can both filter and replay the network diagram using a time-scale slider. They should also have the capability to generate an aggregated summary network within specific time windows, be it by frame, day, week, or month. Additionally, the marking feature can aid in analyzing primary delivery routes or tracking delivery trajectories for specific products or equipment. A summary of these mappings is provided in the Figure 4 below.

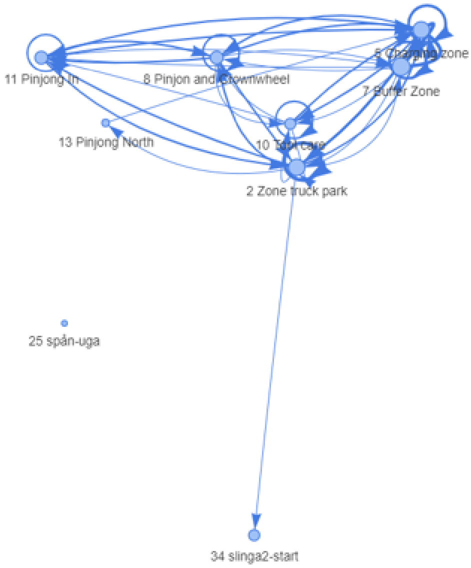

Figure 3. A network diagram of material flow based on SPL data

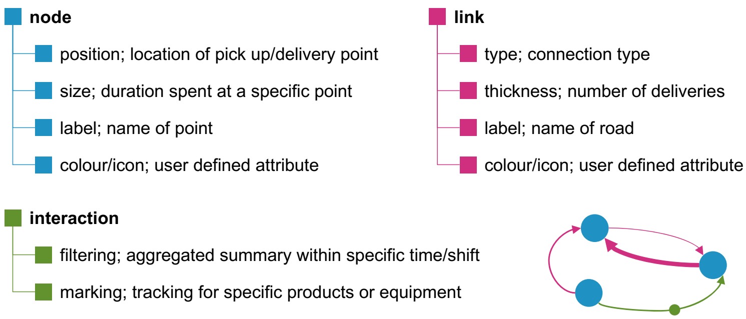

Figure 4. An example of mapping between network diagram and SPL elements

5.2. *Managerial implications of visualizing SPL data*

The visualization of SPL data transcends its technical merits, offering a spectrum of managerial implications deserving of thorough consideration. Dynamic visualization of SPL data equips managers with real-time insights into operations. This immediate transparency facilitates swift, informed decision-making, drastically reducing potential downtime and optimizing productivity. Further, visual representations, notably those that permit filtering and highlighting specific nodes and paths, serve as a conduit for managers to pinpoint bottlenecks, recognize underutilized resources, or discern overburdened segments within the system. These visual insights steer the optimal allocation of resources, encompassing both equipment and workforce considerations.

Moreover, the visual framework simplifies communication, bridging gaps among diverse stakeholders. Whether inter-departmental exchanges or conversations spanning the managerial to operational spectrum, consistent visualization assures alignment, cultivating a spirit of collaboration and synergy. Delving into patterns and trends within the visualized data empowers managers to forecast forthcoming challenges and opportunities.

An added boon is the adaptability of visualization tools. Tailored to meet specific user needs and preferences, this customization caters to managers across roles, ensuring they interface with data in the most pertinent and actionable manner. Furthermore, the interactivity inherent to SPL data visualization is a catalyst for continuous improvement. By revisiting specific scenarios or zooming into chosen time frames, managers can dissect challenges, pinpoint their genesis, and strategize for sustained operational betterment.

6. Conclusions

This study introduced a framework that synergizes SPL with network diagrams, enhancing the visibility of material and information flows in manufacturing material handling. Drawing from a case study in the automotive sector, our research yielded two pivotal theoretical contributions. First, the study provided a detailed characterization of the components within network diagrams that visualize spatial-temporal data pertinent to material handling in manufacturing. Second, it offered valuable insights for managers overseeing the planning and implementation of tasks related to the movement of material and information.

However, two key limitations surfaced in our research. The initial limitation pertains to the absence of a spatial-temporal relationship encapsulating the components of SPL. Accordingly, future research will focus on developing dynamic network diagrams that uncover concealed behaviours and patterns from digitally generated data and evaluate performance based on the spatial-temporal relationships of resources. The second limitation stems from the lack of sustainability parameters assessing the efficacy of SPL within network diagrams. Future research could expand on this scope an include the social, environmental, and economic aspects of sustainability in the movement of materials and information inside the physical boundaries of factories.

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