Knowgraph-TT: Knowledge-Graph-Based Transit Time Matching in Semiconductor Supply Chains

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Abstract—**The semiconductor supply chain is characterized by a global and complex production network in a competitive market. The time when work at one location ends and can be resumed at another is defined as Transit Time (TT). Therefore, planning Transit Time accurately and minimizing delays is crucial as it is used in the execution system to determine the Available to Promise (ATP) and thus important for daily order confirmation. By determining the ATP, the customer receives a response to the resource availability and a due date to the customer requests. Due to tool inherent differences, we choose semantic integration via Knowledge Graph (KG) to match the planned TT used in the execution system and the actual TT measured in the monitoring tool. KnowGraph-TT thereby serves as a role model for further matching and alignment tasks using KG. It connects actual and planned TT, highlights the gaps via applied queries, and enables an optimized update of planned TT. With our solution, deviations of actual and planned TT can be minimized and confirmations of unrealizable deliverable times are avoided.**

Index Terms—**knowledge graph, semiconductor, order management, transit time mismatch**

I. Introduction

The semiconductor industry is competitive with a dynamic market characterized by time-intensive processes [9]. Especially in this highly competitive domain, semiconductor companies strive to offer the highest quality to their customers which implies sustaining delivery reliability. Reliable deliveries are important as customers depend on the delivery promises and their further production steps are based on this commitment. To achieve planning dependability, it is important to implement precise and reliable planning processes. The key to better planning and to foresee delays is to examine Transit Times (TTs). Transit time is the time taken to move goods physically between different locations in a supply chain or laterally to another facility [21].

Supply Chain (SC) integration, as well as the flow of information SC are essential for carrying out effective exchanges between parties [15], thus can enhance SC planning. Semantic data integration enables combining SC data from disparate sources and consolidating it into meaningful and valuable information.

In this paper, we present Knowledge-Graph-based TT matching (Knowgraph-TT), aligned with existing approaches solution that matches transit times of different data sources based on semantic data integration to minimize and prevent delays. Knowgraph-TT leverages a well defined ontology to model TTs. Via KnowGraph-TT, delays are identified and data is kept up to date through semantic transit time matching to create more reliable planning processes within the SC.

The remainder of the paper is divided as follows: After an introduction, section II covers the relevant background knowledge and the need for TT matching. section III describes related approaches for data integration in SC and the gap that motivates the use of semantic data integration for TT matching. section IV contains the implementation details i.e., the ontology modelling, mapping to data sources. The semantic data integration process is shown with an example of two tools that store transit time based on different definitions. section V is the evaluation of the implementation. We rely on competency questions and SPARQL and we discuss the results. Finally, the work is rounded off with section VI where we conclude and discuss the next steps about further analysis in which external factors like a pandemic are addressed.

II. Background and Motivation

In this section, we present the necessary background knowledge e.g., order management, transit time and the need for TT matching.

A. Transit Time

Transit time is the time taken to move goods physically between different locations in a supply chain or laterally to another facility [21]. We distinguish between the actual and the planned transit. The first is the time needed to deliver particular products to the customer. While the planned transit time on the other hand is the time that is expected and planned for future deliveries to the customer. The planned transit time is used to determine the Available To Promise (ATP) which is important for daily order confirmation.

Figure 1 shows that the actual and the planned transit time might be split into several small time intervals and might be in different tools (e.g. one for measuring and one for planning) and are measured and calculated differently. Despite one definition of transit time, the actual and the planned transit time might be in different tools as they reflect different parts of the supply chain. The focus of the planning tool is to plan transit times, while the focus of another tool, e.g., an internal logistics monitoring tool, is to track actual transit times.

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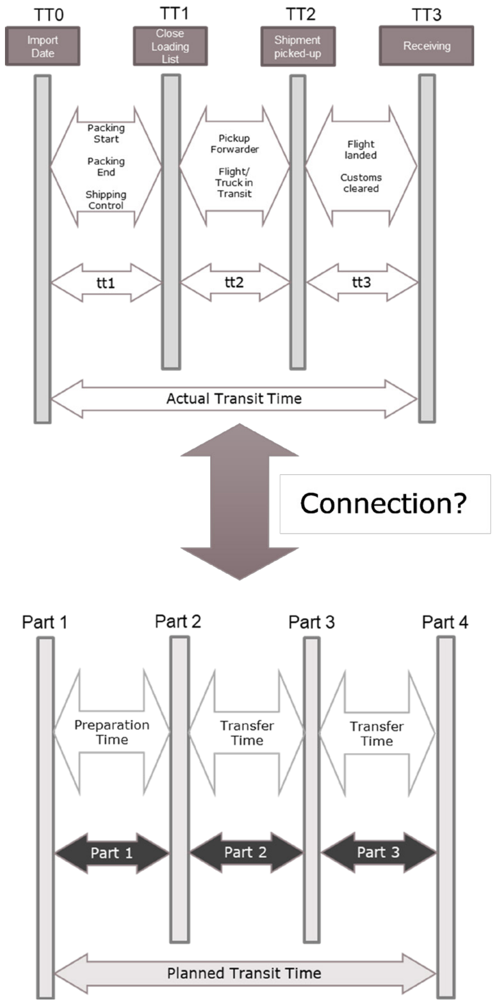

Fig. 1. Definition of Actual and Planned Transit Time.

Namely, within the tools, transit time is measured differently which leads to difficulties in matching the information and keeping it up to date. One example is the divergent interpretation of geographic data. In one tool, transit time is based on facility level and is measured as actual transit time and in the other tool, transit time is based on location level and measured as planned transit time. Transit times need to be accurate and therefore, a matching of the planned transit time and the actual transit time is needed. The matching results in an avoidance of order confirmations to unrealizable ATP's.

B. *Transit Time Matching*

When a customer requests products from the order management (OM), the divisional model (DM) checks whether and when the request can be fulfilled. All involved parties rely on the ATP and it is of special importance for the customer. [7]. Since the ATP is defined by the planned transit time at the time when the goods are sent out by backend (BE), it is important to detect deviations between actual and planned transit time early on and keep plan transit time up-to-date. After creating an ATP, the DF (Demand Fulfillment) confirms on a daily base the Orders and Order Management (OM) sends an Order Promise (OP) to the customer. Thus the OP is based on the ATP which uses the planned transit time. With the OP, the delivery date becomes binding. By then, the customer trusts that the products will be delivered on time.

Figure 2 shows an example of the mismatch between the actual transit time and the planned transit time. The x-axis is the time course and on the y-axis are different blocks each describing a scenario. The first block is the *Plan (Weekly)* describing that 100 pieces are planned to be delivered to the distribution centers (DC) every Sunday, i.e., on weekly basis. The distribution center is a core part of a supply chain and connects factories and retailers [10]. An Available To Promise (ATP) of 100 pieces can be served from Sundays – it was committed from the factory, the factory gets measured on it and it has some buffer in it.

The second block is the plan at the *point of shipment* when the weekly plan is broken down on a daily basis. Within a planned transit time of three days, it is planned to transit the products from the backend on Monday to the distribution centers on Thursday. Backend is part of the chip production process and involves the steps of assembly, test and shipment to the DC. However, when it is shipped from backend the commitment with buffer is replaced by a calculation being the shipment date + planned transit time. So assuming that 50 are shipped on Monday with a planned transit time of 2 days, the ATP of 100 on Sunday is reduced by 50, which are expected on Wednesday (Monday shipping date + 2 days planned transit time). In the daily rerun of the order confirmation, these 50 are used and orders are brought forward.

Actual scenario in the third block shows, that the actual transit time takes longer than the planned one and the planned scenario is not fulfilled. Thus, the planned transit time does not correspond to the actual transit time. Now when the actual transit time is not 2 days but 4 days the brought forward orders need to be delayed as the goods are not coming on Wednesday but on Friday (= shipping date + 4 days actual transit time).

The fourth block is the *Communication to Customer*. The order management creates an availability commitment to the customers on Monday and communicates that the order will be shipped on Thursday. Thus, the customers can expect, that they will receive the products in three days. If the promises cannot be kept, it potentially leads to customer dissatisfaction. A deviation between the target and the actual transit time causes planning difficulties for all parties involved. For example, the production site or the customer has no planning certainty when promises are postponed. Therefore, it is important to correlate and match transit times.

III. SEMANTIC DATA INTEGRATION FOR TT

A. *Related Work*

1) Approaches for TT planning: There are various approaches to planning and optimizing transit times within a supply chain. One example to improving supply chain performance from the retail supply chain is the use of Radio

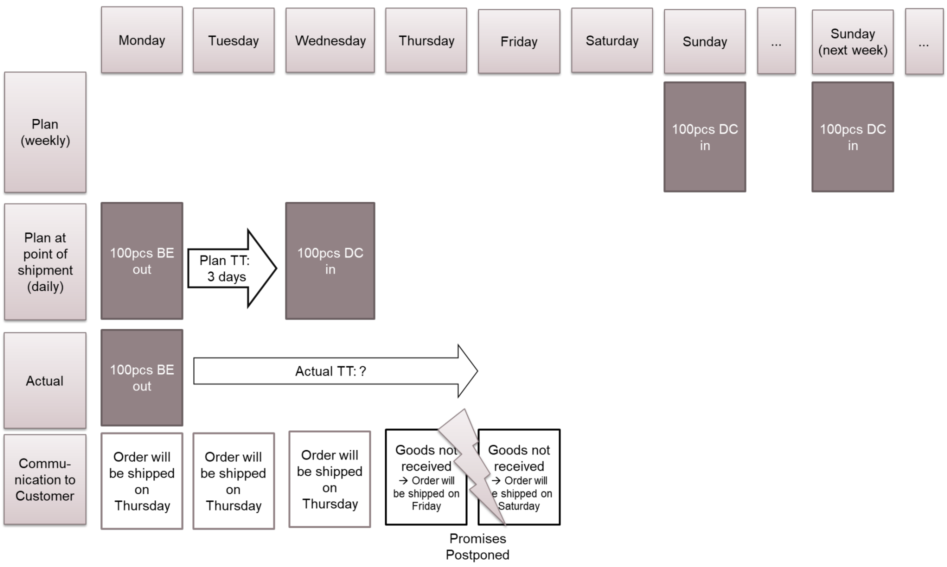

Fig. 2. Transit time mismatch.

Frequency Identification (RFID) technology. The technology is used to increase communication and information transparency between an object and other systems or software (e.g. ERP system) along the supply chain [17]. Methods like forecasting and simulation are also options for the planning and optimization process. The problem remains that the different information provided by such technologies cannot be compared directly. Data integration allows the alignment of data from different data sources.

2) Traditional Data Integration: One of the popular approaches to data integration is Extract Transform and Load (ETL). [20] provides a survey about traditional data integration and ETL techniques. Authors identify that ETL tools show limited ability is available to extract data from different sources at the same time. Moreover, without this domain knowledge, it is impossible to extract, transform and load. Semantic technologies are used to further enhance definitions of the ETL activities involved in the process [14]. Ontologies provide a common vocabulary for the integrated data and generate semantic data as part of the transformation phase of ETL. Semantic data integration is aligned with traditional data integration techniques. It can be referred to as Semantic ETL.

B. Semantic Data Integration

We rely on the ontology-based data access (OBDA) approach for semantic data integration. The schema is given in terms of an ontology representing the formal and conceptual view of the domain [8]. Also, we use ontology merging to overcome challenges such as the various definitions of location. A knowledge graph refers to a semantic network of concepts, properties, individuals and links representing and referencing foundational and domain knowledge relevant for a domain [5]. By creating the knowledge graph that is connecting different data sources, the data can be visualized and analyzed without changing the original data sources. Therefore, redundancies can be avoided and the data is connected. Flexibility can be increased by having the possibility to implement changes on the data or adding new data sources. Semantic models are characterized with easy extendibility which makes them significant to the agile supply chain domain. In addition, this method of data integration achieves interoperability and information transparency. This type of data integration is particularly relevant in domains where data models are diverse and entity properties are heterogeneous [13].

IV. IMPLEMENTATION

In this section, we show KnowGraph-TT: applying semantic data to match the transit times of two tools of a multinational semiconductors company.

A. Ontology Modeling

The basis for the process KnowGraph-TT is to acquire different sources of transit time. Two different sources that manage transit time are found and analyzed. In the following, the sources are referred to as Tool A and Tool B. Tool A is equivalent to the executing tool while Tool B corresponds to the monitoring tool.

Firstly, Tool A stores the actual transit time on location level. The transit takes place from one location to another. Therefore, the location shipped from and the location shipped to are important concepts for the matching process. The class "TT_Actual" represents the Actual Target Time to ship a product from the location "ShipFrom_Loc" to the location "ShipTo_Loc".

Secondly, Tool B records the planned transit time on a facility level. Here, the transit takes place between two facilities. The planned transit time is the time it takes to ship the products from the finishing facility to the expecting facility. It is similar to the structure of Tool A. The class "FTRN_TRANSIT_TIME" is the planned transit time it takes to ship products from "FAC_FACILITY_NAME_FROM" to "FAC_FACILITY_NAME_TO". Each facility is identified by the class "FAC_FACILITY_NAME" which is important for the matching of locations in the location ontology.

As transit times are provided in various ways and they can not be matched directly, an additional intermediate ontology is necessary. Therefore, the location ontology, Figure 3, aligns the concepts of locations to be able to compare the different transit times with each other. Here, one location can have multiple facilities. Therefore, a location key is assigned to each facility so facilities and locations can be compared with each other.

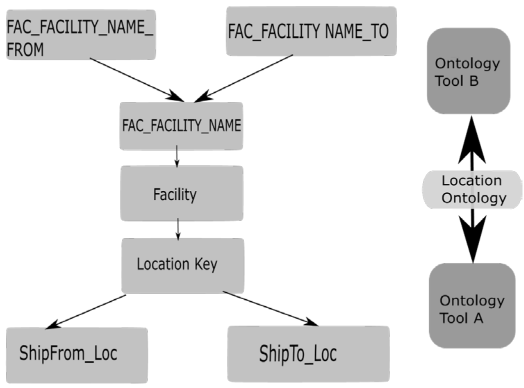

Fig. 3. Single Location Ontology.

B. Ontology Merging

Figure 4 shows the individual ontologies and the merged ontology. The output merged ontology is referred to as the semantic abstraction layer, it represents the schema of the domain. It contains the main concepts and relationships of the transit time domain. We rely on this to map data from different data sources and match TT.

The left side, is the ontology for the *Actual Transit Time in Tool A*. While on the right is the ontology for the *Planned Transit Time in Tool B*. Lastly, the *Location Ontology* is depicted in the middle part in Figure 4. Each facility from Tool A is uniquely identified by the class "LocationKey". The matching between facility and location is explained in more detail in Figure 3. Figure 3 translates the facilities from Tool A to the locations in Tool B.

C. Mapping

After generating the semantic abstraction layer, the next step is to connect the data sources from the different tools to the merged ontology. For this step, the tool Protégé plugin "Cellfie" [19] is used. This is used because Protégé is an open source tool and therefore a common used tool. It creates instances out of the given data for every class contained in the given data sources. The semantic abstraction layer contains multiple triples. Each of those triples consists of a subject, predicate and object. For the TT ontology one example triple looks as follows:

V. Evaluation

In this section we evaluate the implementation and show the outcomes of the semantic data integration for TT matching.

A. Setup

The output of the implementation is a knowledge graph that contains the ontology (Figure 4) along with the materialized triples as shown in the mapping. We rely on SPARQL [18] queries to evaluate the knowledge-graph. We upload the knowledge-graph on Apache Jena Fueski Server and execute the queries.

The choice of this methodology for evaluation is driven by the fact that SPARQL is a standard that allows to express queries across diverse data sources. SPARQL can be used to query external data sources e.g. weather reports to add explainability and find a correlation between TT mismatch and bad weather conditions. Also, in case we wanted to attribute the mismatch to locations geospatial SPARQL allows to represent geospatial data is using GeoSPARQL, which is an RDF vocabulary and a set of extensions to SPARQL to support spatial queries. The results of the queries are discussed below. It is important to mention, that the transit times are given in hours. Also, the transit time data is partially extracted from the tools to illustrate the methodology.

B. Queries and Answers

For conciseness we show the Competency Questions (CQs), representing the SPARQL queries but in natural language. We refer to a GitHub repository for detailed queries. CQs are a set of requirements on the content as well as a way of scoping and delimiting the TT matching problem.

CQ1: What are the planned transit times and average actual transit times for delivery routes between locations?

Firstly, all delivery routes that address the same location are grouped. After summarizing the deliveries of the same routes, the corresponding actual transit time is averaged. For each route, the planned transit time is compared to the average actual transit time. Possibly, different planned transit times are assigned to an average actual time because several facilities can be related to one location. Results in Figure 7(a) provide an overview of the results from the query evaluation. For example, the average actual transit time of 295 hours differs from the planned transit time of 165 hours. It can be seen that within the same delivery route, there are large deviations in the average actual transit time and the planned transit time.

CQ2: What are the actual transit times and its planned transit time for a certain delivery route between locations?

This query filters one delivery route between two locations. Here, the planned TT is compared to the actual TT. Since different facilities are assigned to one location, various facility delivery routes exist within one location delivery route. This means, that several actual transit times are related to one

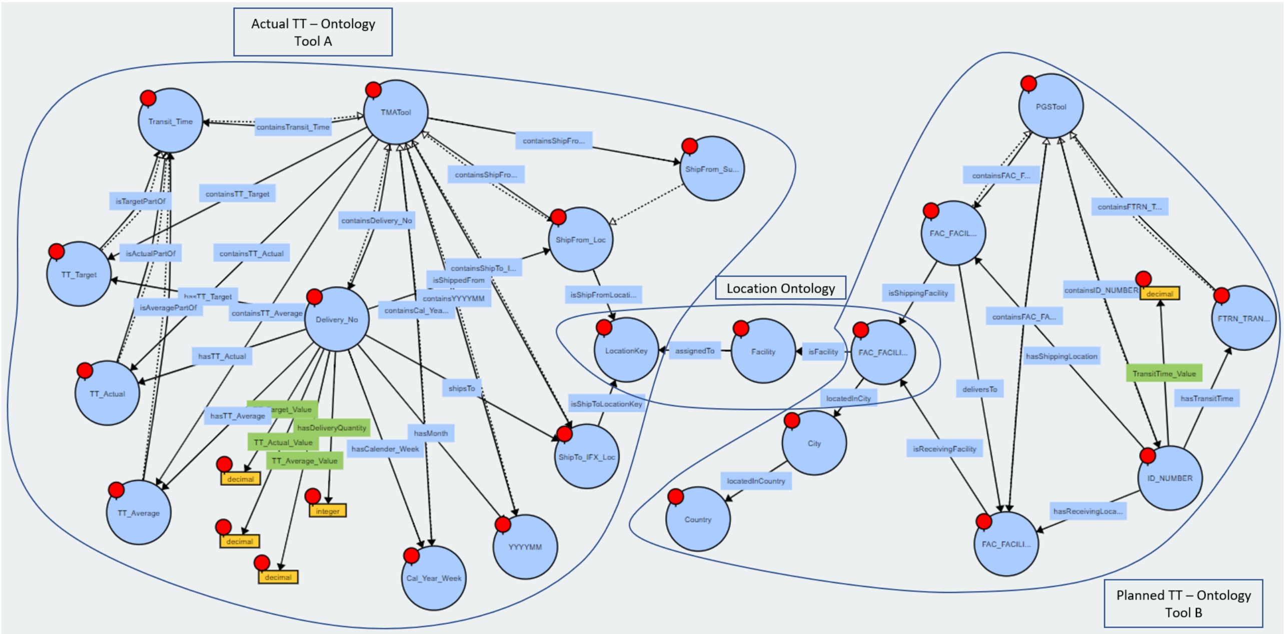

Fig. 4. Transit Time Ontology matching in the Measurement Tool for Actuals and in the Base Data Tool for Planning purposes.

Fig. 5. Triple City.

Fig. 6. Triple Facility.

planned transit time. Based on this delivery route, the actual TT is compared to the planned TT.

The query result is represented in Figure 7(b). The resulting planned transit times are 48 hours and 120 hours. Nevertheless, the actual transit times for the delivery route vary from 51 hours to 82 hours. The interval from 51 to 82 hours of the actual transit time shows, that there are large fluctuations between transit times.

CQ3: What are the actual transit times and its planned transit time for a certain delivery route between facilities?

This query only filters one shipping and one receiving facility. The results in Figure 7(c) show, that the planned transit time within this delivery route is 48 hours. Furthermore, the actual transit time may vary from 51 to 82 hours. Figure 7(c) shows, that the deviations between planned transit time and actual transit time are not as large as in CQ2.

CQ4: What are the highest and lowest transit times of certain delivery routes?

In this query, the plan transit time, average actual transit time, and both the minimum and maximum actual transit time are compared with each other. The results in Figure 7(d) show the big difference between the maximum and the minimum actual transit time. One example for a query result is a delivery route with a planned transit time of 72 hours, an average actual transit time of 62 hours, a maximum of 71 hours with a minimum transit time of 45 hours. One reason for the fluctuations is that several facilities are located in one location. Thus, according to one plan transit time, there are various actual transit times.

CQ5: For which transit route is the actual transit time higher than the planned transit time?

In this query, the plan transit time is compared to the actual transit time. Some deliveries are stated several times when different planned transit times are given. Finally, the deliveries are filtered which in reality took longer than planned. In Figure 7(e) the query results show, that in several cases the actual transit time is higher than the planned transit time of the delivery route.

CQ6: What location transits have the highest discrepancy between planned and actual transit times? (Ordered by discrepancy)

This query relies on the transits between locations. For each transit, the actual transit time, maximum planned transit time, and discrepancy obtained from the actual and planned transit times are given. The result table in Figure 7(f) is ordered descending by the discrepancy. The highest discrepancy for this data is 820 hours with an actual transit time of 928

Fig. 7. Chart visualization of the SPARQL query results for various Competency Questions (CQs).

discrepancy of 820 hours between the planned transit time and the actual transit time shows how unreliable the key figures can be sometimes.

C. Results & Discussion

The implemented approach combines the planned transit time used in the execution system and the actual transit time measured in the monitoring tool. The queries, which are evaluated in section V highlight the gaps between planned transit time from different viewpoints. The results show, that the gaps of TT matching between location routes are larger than the gaps between facilities. One possible explanation is, that different facilities can be assigned to one location. Therefore, different actual transit times are assigned to one planned transit time. Based on the query results, it could be shown that a timely update of planned transit times can be enabled as well as unachievable order confirmations are avoided.

In this paper, two tools were successfully connected using semantic data integration to combine the distinct interpretation of transit time and to enable the analysis of the consequences of the mismatch. Semantic Data Integration is applicable in other Supply Domains to integrate dispersed data sources. We can rely on the proposed location ontologies to extend to other domains e.g., Customer Relationship Management, Revenue Management as per [16]. Also, the semantic abstraction layer secures a common understanding of the domain in question, thus entails interoperability and extendibility. However, the approach has some limitations. First, KnowGraph-TT provides a self-created location ontology, thus missing the re-usability characteristic of ontologies. We did not re-use standard ontologies representing the location. Moreover, for the evaluation KnowGraph-TT is not evaluated versus other existing approaches or related work. We only used CQs for the evaluation to ensure that the output Knowledge Graph covers the domain in question, and enables the transit time mismatch analysis.

VI. CONCLUSION & OUTLOOK

In a competitive market, semiconductor manufacturers seek to offer the highest quality to their customers and rely on an accurate and reliable supply chain planning and commitment. In this work, we propose KnowGraph-TT to connect plan- and actual transit times on different definitions and tools via semantic data integration. Based on this, we apply this KnowGraph-TT to a use case of an international semiconductor manufacturing firm. The use case was evaluated successfully via competency questions in highlighting actual-versus plan transit time mismatches. Incorrectly planned transit times are the cause of ATP postponements and negative Early Warnings (a negative Early Warning is when a previously committed delivery date is postponed), but by far not every violation of a planned transit time in the internal supply chain causes an Early Warning. Thus, we can examine now the extent of the effect of time violations as a root cause of ATP postponements and negative Early Warnings. Consequently, we can study how to update the planned transit time concerning actual transit times to create a non-conservative and reliable demand fulfilment. In future work, we aim to analyze the effect of external factors on the supply chain. We intend to extend the knowledge graph capabilities to effects like the pandemic, which strongly influences the supply chain processes. This should enable us to correlate the transit time mismatch with COVID-19 reports, to be able to proactively change the plan transit times before violations happen.

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