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Framework for the usage of data from real-time indoor localization systems to derive inputs for manufacturing simulation

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Abstract

Discrete event simulation is becoming increasingly important in the planning and operation of complex manufacturing systems. A major problem with today's approach to manufacturing simulation studies is the collection and processing of data from heterogeneous sources, because the data is often of poor quality and does not contain all the necessary information for a simulation. This work introduces a framework that uses a real-time indoor localization systems (RTILS) as a central main data harmonizer, that is designed to feed production data into a manufacturing simulation from a single source of truth. It is shown, based on different data quality dimensions, how this contributes to a better overall data quality in manufacturing simulation. Furthermore, a detailed overview on which simulation inputs can be derived from the RTILS data is given.

Keywords: real-time indoor localization system; input data management; cyber-physical system; manufacturing simulation; digital twin

1. Introduction

The recent development towards smaller lot sizes presents new challenges for job shops, as they are confronted with a more diversified range of orders [1,2]. To stay competitive, it is necessary to adapt production systems more and more frequently to the dynamic and complex environment [3]. Due to complex interdependencies, the impact of adaptation measures in manufacturing systems is difficult to predict by humans [4] and real-time discrete event simulation is becoming increasingly important as a decision-support tool [5,6]. The success of discrete event simulation applications relies on high-quality production data [7]. With the rise of cyber-physical systems (CPS), there will be a better vertical connectivity from sensors on the shop floor to data storage, processing and analytics in the cloud. The real-time availability of production data enables various data-based services [8,9] and provides great potential for production optimization [10,11].

Sequential procedures for creating discrete-event simulation are part of different established standards [12]. An essential step in these procedures is data collection, which to this day includes time-consuming interviews or workshops with production employees and experts [13]. However, this best practice has the disadvantage that the collection of quantitative values such as process times or machine availability by interviewing people is subject to their individual perception [14]. Because of their experience, they can estimate an average but neither the distribution nor the function that represents the actual underlying context. Such inaccuracies in the creation and parameterization of simulation models should be avoided, to be able to make more reliable statements with the simulation. Therefore, this paper examines the potential of data from real-time indoor localization systems (RTILS) to improve data quality in manufacturing simulation by deriving simulation inputs from data rather than questioning people about them.

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1.1. Data quality issues in job shops regarding manufacturing simulation

Nowadays, a large amount of data is already available in real-time, but the key question is whether it is also the "right" data for the simulation use case. Fact is, that the systems that collect the data have not been designed for the requirements of a simulation [7,15]. A lot of data is gathered by machine data acquisition (MDA) and production data acquisition (PDA) systems and is stored in heterogenous systems such as the manufacturing execution system (MES) or enterprise resource planning (ERP). Usually, *inconsistencies* occur, and it cannot be easily decided which source of data should be trusted [11].

Besides, *completeness* of data is another issue, as there is still a lack of high-quality data that is necessary for the implementation and parameterization of manufacturing simulation models. For example, actual process times are usually not known in job shops, if no feedback data from the shop floor is available and thus, the target times are used instead. Whereby, it is generally known that the deviation between actual and target times in production can be significantly different. Accurate simulation results can only be achieved with accurate data input, known as 'garbage in, garbage out' theory [13].

The *availability* of data for the modelling of manual processes is another challenge in job shops. Automated processes on machines are already well monitored, whereas the indirect manual processes are not good mappable due to their stochastic behavior [1]. In addition, the times for manual processes usually must be reported by the employees. The quality of the data therefore depends largely on their work ethic and is inherently prone to errors. Since manual activities in job shop production are indispensable, there are approaches to better understand such activities through the analysis of data from wearable accelerometer and gyroscope sensors with deep neuronal networks [16] and input data modeling [14].

1.2. Hypothesis and methodology

Due to the data quality issues in job shops mentioned above, the hypothesis of this work is that it is beneficial to derive inputs for manufacturing simulation by using data from RTILS to contribute to a significantly higher overall data quality in manufacturing simulation. Furthermore, if the time-consuming phase of data collection and processing is shortened, more scalable solutions can be developed for manufacturing companies. Here, the focus is on the sheet metal industry, but the results are easily transferable to any job shop production in other industries.

The structure of the paper is as follows: In Section 2, the indoor localization system under consideration is introduced and a differentiation from previous work is given. In Section 3, the important information models for manufacturing simulation are presented. In Section 4, the idea to use RTILS as main data source for manufacturing simulation, will be introduced within the framework of a cyber-physical production system. Besides, the required inputs for the manufacturing simulation for sheet metal industry are collected and the usage of RTILS to derive them is discussed.

2. Potentials of real-time indoor localization systems

A recent survey on the potentials of indoor-localization in production revealed that many data-based services would profit from a manufacturing simulation [17]. However, data from RTILS are not yet considered as main input for manufacturing simulation. In the following, a production order consists of a number of equal parts which corresponds to the lot size.

2.1. Indoor localization system for sheet metal production

In today's sheet metal production, there are long search times, as the positions of production orders are not known. Each production order can only be identified by its accompanying document, which contains the necessary work steps. With decreasing lot sizes, the number of these documents increases in relation to the actual number of parts. As a result, a single document is difficult to find among many. In addition, they are often misplaced and, after printing, flexible adaptation to changing production conditions is associated with disproportionately high expenditure. To enable paperless production, an indoor localization system was developed that replaces the accompanying documents with so-called *markers*. Markers are mobile devices that can be tracked within a reference system that is made up by a sensor network of stationary *satellites*. In sheet metal production, special conditions prevail for RTILS due to reflections from shiny metal surfaces. Ultra-wideband technology (UWB) using triangulation has proven to be a suitable technology for precise localization under such conditions and is therefore the technology of the considered RTILS. Well-structured overviews can be found in the literature, if there is interest in localization technologies [8,18].

Before the markers are released into the manufacturing system, they need to be initialized by assigning a unique object ID ($\mathrm{ID}_{\mathrm{object}}$) to the unique marker ID ($\mathrm{ID}_{\mathrm{marker}}$). Each event sample from the RTILS data is a state vector that is structured as follows:

$$s_{\mathrm{RTILS}}(t) = \left(x, y, z, \mathrm{ID}_{\mathrm{marker}}, \mathrm{ID}_{\mathrm{object}}, \mathbf{C}\right),$$

where x, y and z are the cartesian coordinates in the reference system of the satellites. This state vector can be enriched with any context information $\mathbf{C}$ e.g. the process plan, production layouts or the geometry of the orders' parts. Stringing together the positions from the RTILS over time, trajectories of the material flow are known.

2.2. Differentiation from previous work on the use of indoor localization data as input for manufacturing simulation

So far, RTILS had no central role in input modelling for manufacturing simulation, especially not in the sheet metal industry. In the last years, RTILS were still under development and have been used only on a test basis in realistic operation, since the industrial requirements like immunity to interference of radio signals, security and a high degree of availability are demanding [19]. Hence, realistic data sets for assessing how simulation inputs can be derived, are lacking.

There are few approaches in literature, where some of the inputs for a discrete event simulation of a manufacturing system are derived from position data. Frazzon et al. [20] introduced a data exchange framework based on common IT structures for a data-driven adaptive simulation-based optimization to determine feasible production schedules. The real-time data is gathered with gates that automatically book job arrival and processing times. This data is then forwarded to the MES via a MDA and a PDA system. Altaf et al. [21] used radio-frequency identification (RFID) to collect production data for simulation input modelling. With the historic data, they were able to fit distributions for process times in a production line for prefabricated walls.

Tao et al. [9] propose to track positions of products with RFID for a future case of shaft manufacturing. Intelligent material tracking is according to them a key technology for digital twin-driven product manufacturing. They also mention simulation as part of their digital twin concept, but do not give any indication of what type of input data is used to simulate the product/machine/manufacturing system respectively and how they want to merge data from heterogeneous sources.

This work distinguishes itself from the previously presented approaches, as the RTILS is regarded as the central main source of data for simulation input modeling. This is technically feasible, because the RTILS under consideration has technological advantages over the RFID-based systems that were under consideration by other authors so far, because:

- a technology with broader communication range is used for locating, namely UWB, that can track the complete trajectories of objects over short and long distances
- the markers are active sensor systems which can control the material flow decentralized through a human-machine interface in form of an e-ink display and color LEDs
- the markers are equipped with additional sensors such as an inertial measurement unit (IMU) and RFID transponder with near-field communication (NFC).

3. Information models for manufacturing simulation

In a manufacturing simulation, pieces of information are required both for the model creation and parameterization. In the following, two established standards are presented, that contain information models for manufacturing simulation.

In 2010, the Simulation Interoperability Standards Organization (SISO) presented the *Standard for Core Manufacturing Simulation Data (CMSD) – UML Model* [22]. Two years later, an additional XML representation was published [23]. Both were developed as part of efforts to improve interoperability between different simulation tools. The focus of the CMSD standard is therefore on the specification of neutral structures suitable for an efficient exchange of data between different simulation environments.

The association of German engineers (Verein Deutscher Ingenieure - VDI) published the VDI 3633 standard [12] that contains an illustration of simulation data categorized in system load data, organizational data and technical data, but is missing further details about the simulation inputs in the text.

There is no common standard that can be used for any manufacturing simulation, especially none that suits different domains [5]. Thus, in simulation studies, information model standards are often extended with user-defined properties [24]. In this work, the existing standards [12,22,23] are extended with the help of expert knowledge to a domain-specific data model for manufacturing simulation in the sheet metal industry.

4. RTILS framework for manufacturing simulation

The basic idea of this work is to no longer regard RTILS as one of many heterogeneous data sources in production, but to give it a central role as a data harmonizer. The data harmonization is achieved by storing the required data for manufacturing simulation in a single data system based on a domain-specific information model from which the real-time manufacturing simulation can be performed (single source of truth). A sensor fusion in the RTILS is applied for simulation *input modeling* to derive as many required inputs as possible from the historical data. There are interfaces to transfer additional information into the RTILS data model, if inputs for the production simulation cannot be derived, e.g. the list of released orders that are required for a forecast of the future workload. The sensor signals can further be used for *real-time parameterization* of the simulation model.

The combination of a manufacturing system and its simulation model via real-time data parameterization and control of the real system through adaptations, as depicted in the green box in Fig. 1, is referred to in the literature as digital twin [25]. With the help of the *digital twin*, it will be possible to simulate and forecast production plans and processes [9]. Thus, the digital twin will serve as an assistance system, where adaptation measures can be played through and decision-makers can get quick support.

An advantage of this approach is its suitability for a typically heterogeneous machine park, since the RTILS framework does not rely on machine interfaces. For example, process times can be derived from RTILS data, which enables benchmarking among machine manufacturers and the calculation of standard values for the initialization of models.

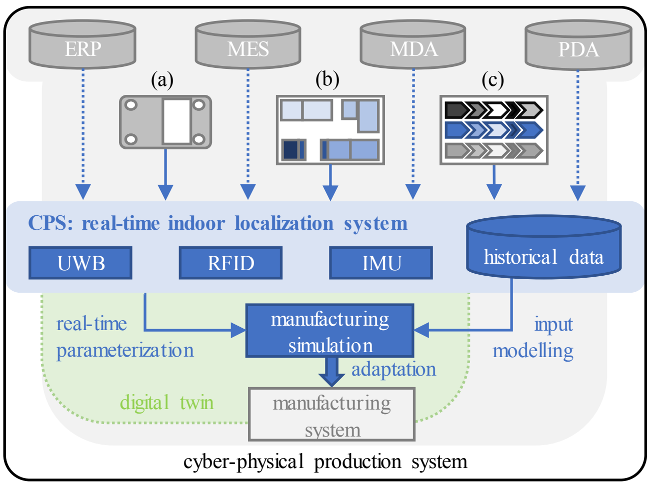

Fig. 1. RTILS framework for a cyber-physical production system with a manufacturing simulation based on a real-time indoor localization system as main data harmonizer. The required pieces of context information are (a) the geometry of parts; (b) the manufacturing layout; (c) the process plans.

There are eleven common dimensions of data quality problems in discrete event simulation [7,15,26], which are accuracy, reputation, accessibility, currency, completeness, precision, relevance, resolution, traceability, clarity and consistency. Table 1 shows for each dimension, how the RTILS framework contributes to an improved data quality in manufacturing simulation.

Table 1. Data quality dimensions [7], their definitions [26] and how the RTILS framework will improve data quality in manufacturing simulation.

Data quality dimension and definition acc. to [26]	Contribution of the RTILS framework to improve data quality
Accuracy Degree to which data possess sufficient transformational and representational correctness	The localization accuracy depends on the technology and the positioning algorithms, here it is in the centimeter range. The accuracy of the derived input variables for the simulation depends on the selected analysis method.
Reputation Degree to which data are trusted or highly regarded in terms of their source or origin	In contrast to manual feedback from the worker about e.g. process times, the data is automatically recorded and analyzed, which makes the data more trustworthy.
Accessibility Degree to which data are available or easily and quickly retrievable	The RTILS data is easily and quickly retrievable from a server on premise or from a cloud provider.
Currency Degree to which the age of the data is appropriate for the use of the data	Real-time data is always up to date and when historical RTILS data is used for analysis purposes, attention is paid to structural changes in the system.
Completeness Degree to which all parts of the data are specified with no missing information	The RTILS complements the previously used, mostly static data with dynamic movement data. Thus, fewer interviews are required to obtain simulation inputs.
Precision Degree to which data possess sufficient number of significant digits in their numerical values	The RTILS provides enough significant digits, since the positions are accurate to the centimeter, which is sufficient for the localization of objects with a size ranging from several centimeters to meters.
Relevance Degree to which data are applicable for use	The position data reflects the dynamic behavior of the production system and is thus highly relevant for simulation.
Resolution Degree to which data possess sufficient level of detail	The data is gathered with approx. 1Hz, whereas the average duration of processes is usually in the range of minutes.
Traceability Degree to which data are easily attributed to a source	The RTILS as data harmonizer knows the sources from which the data is obtained, as there are clearly defined interfaces.
Clarity Degree to which data are unambiguous and understandable	The raw data from the RTILS requires procedures for data analysis and suitable visualization techniques to be understandable.
Consistency Degree to which (a) data are specified […], and (b) any one data value does not conflict with any other	The RTILS acts as data harmonizer and provides one single source of truth. The specification of the common data model, defining the terminology, is a central element of the RTILS.

4.1. Required simulation inputs for manufacturing simulations in the sheet metal industry

The evaluation of how data from RTILS can be used for deriving inputs for a manufacturing simulation can be found in the tabular overview in Fig. 2. The rows 1–45 list the required simulation inputs for a manufacturing simulation in the sheet metal industry, that were identified from the literature extended by domain-specific expert knowledge (see entries in italic letters). The categorization into system load data, organizational data and technical data is adapted from [12].

The origin of each simulation input is indicated with a cross in the columns under (a). The next two columns under (b) show whether an input is more likely needed for the creation of the simulation model or for its parameterization. It becomes obvious that the system load data is only used for latter. The columns under (c) suggest, where the derivation with the help of the RTILS data should be investigated. Here, a distinction is made between an analysis in real-time (RT) or based on historical data (H). Column (d) shows additional context information that is needed for the derivation of the simulation inputs. Interfaces or new sensors are necessary for inputs, if the respective input cannot be determined solely from the RTILS data, see column *other*. The last column (e) shows that not all necessary pieces of information for the simulation are available in MES or ERP systems. This motivates again the use of RTILS data to complete the missing inputs and thus to improve data quality in manufacturing simulation.

4.2. Discussion of the usefulness of data from RTILS for the derivation of simulation inputs for manufacturing simulation

There are many simulation inputs for which the consideration of RTILS data shows great potential, especially when no information is available up to now. In general, the inputs can be derived more easily, if the variable being searched for is location-related, e.g. the start and destination of transport orders (rows 6 & 7). If there is no location reference, this does not imply that the inputs cannot be derived. For example, the quantities (row 5) can be determined by counting trajectories with the same order IDs. The inputs that have been classified as not derivable from the RTILS must be queried via interfaces or via the consideration of information from additional sensors. For example, the unique order ID cannot be derived and must therefore be assigned to the respective marker ID via an interface at the beginning of production.

During the preparation of the table, recursions were noticed e.g. in the determination of process plans and geofences. The process plan can be derived from historical trajectories of the UWB data using geofences, whereas the geofences can be approximated, if the process plan is known. To resolve this recursion, geofences should be defined in a way that an unambiguous allocation of processes to locations is made possible. This will be especially important to identify strategies and dispatching rules (rows 25–28). Today, the definition of geofences is done manually by experts drawing in the layout plan of the manufacturing system, but in the future, geofences could be a result of advanced analyses of the RTILS data.

			No.	Input	a origin: VDI 3633 [11]	a origin: CMSD [21,22]	a origin: *domain-specific*	b use: model creation	b use: parameterization	c RTILS: UWB	c RTILS: IMU	c RTILS: RFID (NFC)	d interfaces: layout / geofences	d interfaces: process plan	d interfaces: others	e: MES or ERP
system load data	input of orders	production orders	1	*order date*			X		X						X	X
			2	order release		X			X						X	X
			3	order due date	X	X			X						X	X
			4	order ID		X			X						X	X
			5	quantities	X	X			X	H				X		X
		transport orders	6	*departure point*			X		X	RT						
			7	*destination*			X		X	H			X	X		
	product data	*per order ID*	8	bills of material	X	X			X						X	X
		per individual part number	9	material (sheet metal type)		X	X		X						X	X
			10	*part geometry*			X		X						X	X
			11	sequential process plan	X	X			X	H			X			X
		per process step number	12	type of process step		X			X	RT	O	O	X			X
			13	actual process time		X			X	H	H	O	X	X		(X)
			14	job assignment		X			X	H						X
organisational data	working time organisation	breaks	15	list with break times	X	X			X	H			X			(X)
			16	maintenance schedule		X			X	H			X			(X)
		shift model	17	for workers and machines	X	X			X	H			X			(X)
	allocation of ressources	workers	18	list of workers	X	X		X		H					X	X
			19	worker-process-allocation		X			X	RT			X	X		(X)
		machines	20	list of machines	X	X		X							X	X
			21	machine-process-allocation		X			X	H				X		(X)
			22	sequence-related setup times		X			X	H	O	O	X			
		conveyor system	23	list of transportation ressources		X		X							X	X
			24	transport system-part-allocation		X			X	H						
	structural organisation	strategies	25	*dispatching rules*			X	X		H			X			
			26	*temporal safety buffer between successive process steps*			X	X		H			X	X		(X)
			27	*warehousing and storage*			X	X		H				X		
			28	express order handling		X		X		H						
		restrictions	29	*access permissions*			X		X	H			X			
		failure management	30	*MTTR, MTBF*			X		X	H						X
technical data	factory structure	system topology	31	hall layout	X	X		X		H				X		
			32	manufacturing equipment	X	X		X							X	
			33	transport functions	X				X	H						(X)
			34	geofences	X		X	X		H				X	X	
	production data	utilisation time	35	for each ressource	X				-	H			X		X	X
		performance data	36	target material utilization			X		X						X	X
			37	for each ressource	X				-	H						(X)
		capacity	38	for each worker and machine	X				X	H	O				X	X
	material flow data	topology of the material flow system	39	*transportation ressources to routes*			X		X	RT			X			
		performance data	40	velocity		X			X	RT	RT					
			41	*battery life of transportation resssource*			X		X	H	H		X			
		capacity	42	*for each transportation ressource*			X		X	RT						
	failure data	functional failures	43	*frequency of faults*			X		X	H						
			44	*durations of faults*			X		X	H						
		availabilities	45	for each ressource	X				X	H						X

Fig. 2. Required simulation inputs for manufacturing simulation in the sheet metal industry; (a) origin of the inputs; (b) use of inputs; (c) inputs that can be derived from the real-time indoor localization system (RTILS); (d) necessary context information to derive inputs; (e) availability of inputs in existing systems. (X) = targets defined; RT = determinable in real-time; H = derivable with historic data; O = optional.

5. Conclusion

The quality of the results of a manufacturing simulation strongly depends on the quality of the input data. It was shown, that RTILS have great potential to improve data quality in manufacturing simulation, especially for determining organizational and technical inputs. A RTILS framework was proposed, in which a RTILS is used as the central instance of a cyber-physical production system. The provision of real-time feedback data from the physical system into the simulation model and the adaptation of the physical system with the knowledge discovered in the simulation, was introduced as the digital twin of a sheet metal factory.

A limit of this work was the focus on the sheet metal industry. For the transfer to other industries, the respective experts must check and adapt the list with inputs. Also, the determination of the presented inputs will rely on standardized processes. The proof, that these are derivable, is ongoing research, but in a first use case, e.g. break times and shift plans (rows 15 & 17) were derived accurately for every working area of the shop floor by analyzing the marker activities in each geofences over time.

In future work, the acquisition of features of the part geometry is very interesting in connection with the process times from RTILS. This can be used to learn predictive models that could replace process time distributions. Of further interest will be the handling of outliers and rare events, the derivation of rules and strategies and the development of suitable methods for data analysis.

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