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Analysis of asset location data to support decisions in production management and control

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Abstract

In the era of cyber-physical environments, indoor asset tracking systems enable to monitor and control production in a smarter way than ever before, as they are capable of providing data about the location of various equipment on the shop-floor in near real time. The right use of this data contributes to the improvement of production control and management processes, however, utilization of the related information often requires novel methods. In the paper, decision-making approaches are presented that rely on advanced data analytics for asset location systems. The efficiency of the results are presented through an industry related use-case.

Keywords: Indoor positioning system; Data analytics; Production management

1. Introduction

With the spread of digital technologies, the opportunity of collecting data in industrial environments is not a serious question anymore, but rather the efficient use of these process-related data in enterprise level decision making processes. Considering the managerial objectives, the key requirements related to the digital technologies are the real business value that they bring, and the associated return on investments. Many new technologies in the prototype and introduction stages have uncertain business-related benefits, as the high-level performance indicators and cost factors depend on the environment in which they are applied. Therefore, the importance of the so-called *proof-of-concept* projects is crucial in the digitalization era, as many new solutions are available and each company seeks for those that best fit in their value chains.

Among these new applications, indoor positioning systems (IPS) have also received higher attention from the manufacturing industry, as they provide the opportunity of tracking and tracing assets in shop-floor environment more efficiently than the previous solutions. IPSs can be used for locating almost any kind of physical asset in a production environment; typical examples are the tracing of products, tools and fixtures. The relevance of accurate positioning might be even higher in production logistics, as transportation resources' routes are usually more complicated to follow than those of the products that can be located by e.g., Radio Frequency IDentification (RFID), where receivers are installed on predefined places. In contrast, tugger trains, automated guided vehicles (AGV) or forklifts can move almost freely on the shop-floor, increasing the complexity to locate them, and optimize their utilization based on their historical paths.

In the paper, novel analytics solutions are presented that enable to utilize IPS data in production management related decision, e.g., to balance assembly lines, predict lead times or optimize the utilization of certain resources. As IPSs usually provide the data in raw or semi-processed formats, advanced analytics methods are often required to obtain the data that is useful for decision makers in the aforementioned processes, furthermore, to increase the internal corporate effectiveness by reducing losses.

The paper is structured as it follows. First, a literature review is provided, focusing on the introduction of recently applied

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IPSs and their utilization in production management and control (Section 2). In Section 3, the problem in question is specified, with the description of the production environment, the nature of the collected data and the results expected. Section 4 provides data analytics techniques that are applied to obtain information to support decision in production management. In order to demonstrate the applicability of IPSs in such decision making processes, numerical experimental results are presented in Section 4.3.

2. Indoor Positioning Systems in Production Environments

In the era of the Internet-of-Things (IoT), smart devices are gaining more attention from the industry, with the aim of increasing the digitalization rate of shop-floor applications [7]. A typical IoT application is the indoor positioning, as it can be applied in several industrial environments, and can be installed already in operating systems. Several technology providers offer accurate IPS solutions, usually relying on ultra-wideband (UWB) technology that enables to achieve up to 2-5 cm accuracy, depending on the environment [15]. Utilizing the fast wireless communication and the accurate asset tracking, IPSs enable to implement scalable and reliable real-time location systems (RTLS) used in warehouse management, fleet management of shop-floor management. As for the physical architecture, a typical IPS is built up of a central data management server that implements the storage and processing of the data, received from the field devices. The latter is a set of tags that are emitting a signal in certain periods, and a set of fix anchors that are capable of receiving the tags' signals, and calculating the positions by using triangulating and/or trilateration functions [5]. The tags are usually equipped with a battery that – depending on the usage – can last up to months with a single charge. Thanks to the small size of an average tag, they can be attached to even small-size products, tools or machines.

As a result of decreasing prices of smart devices, the hardware-related costs of an industrial IPS application are relatively low [11], and the real strength of these systems relies in their scalability and flexibility in terms of use [1]. They enable the digitalization of production systems besides relatively low IT investments, while useful data can be obtained about the product, processes and resources in near real time. In industrial applications, the target shop-floor area is usually subdivided in zones, and the IPS system can determine the zone in which a given tag was in an active state, based on its x and y (and relatively rarely z) coordinates. Although a typical IPS employs advanced signal processing and noise filtering algorithms to assign tags to zones, some further post-processing algorithms [18] are often necessary to derive the target metrics, indirectly from the raw coordinates. Typical data and signal processing techniques – among others – rely on Kalman-filters [2, 12], Monte Carlo [4, 3] and machine learning approaches [8, 13].

The aforementioned metrics are typically utilized in a higher level of the decision making hierarchy, e.g. to derive production control logics, scheduling policies or to improve processes based on actual parameters that reflect the real system behavior. In production management and especially in control, data-driven decisions that consider the actual state of the system at any given point of time are called situation-aware ones. They usually utilize the fusion of a model-based system representation, and the real parameters obtained from the system, so as implementing the digital twin of it. In this way, one can make decisions about the system operation with a foresight on possible outcomes of certain scenarios, without disturbing the operation of the real system. In the paper, the IPS data is processed with the aim of obtaining the real values of some process-related metrics, enabling the later implementation of a situation-aware production control.

3. Problem Statement

In the paper, a data analytics problem in investigated, namely, how spatial data provided by an IPS can be utilized efficiently in production management and control. The positioning system provides raw data about the asset locations over time, and the overall goal is to mine out such performance metrics that characterize the dynamics of the system, considering cycle times, utilization rates and workloads.

3.1. Description of the Production Environment

First, the production environment is introduced where the IPS is operated, and collects data about the products' locations. In the experiments of the paper, a discrete-event simulation (DES) model was used as testbed environment; however, a real industrial use case with the corresponding infrastructure was the motivator of the implementation of the study. Although the original use-case is from the automotive sector, the presented approaches and the applied analytics architecture are not limited to this industrial domain, but also applicable in any discrete manufacturing environment where asset location with IPS can be solved. The simulation model is a realistic testbed of the system in a sense that it provides information about the tracked assets' locations in near-real-time, reflecting the operation of an industrial IPS system. Replacing both the physical production environment and the IT infrastructure of the IPS, the simulation model implements both functions in a single model, and capable of streaming location data towards any application in real time.

As for the processes under study, the DES model of an assembly system was implemented in *Siemens Tecnomatix Plant Simulation*. The overall system consists of four assembly lines that have separated material flows. Therefore, each of the lines can be treated individually by the IPS analytics, without losing any valuable information about the processes. On each assembly line, three main product types are assembled. An assembly line is built up of 15 workstations (WS_1 … WS_15) and all assembly operations are done manually by human operators. The headcount of operators ranges between one to twelve, therefore, output rate and lead times strongly depend on the amount of available manual workforce. In order to avoid blocked processes and smoothen the material flow, part buffers are placed between each consecutive workstations. After the assembly process at WS_11, a functional test is performed and

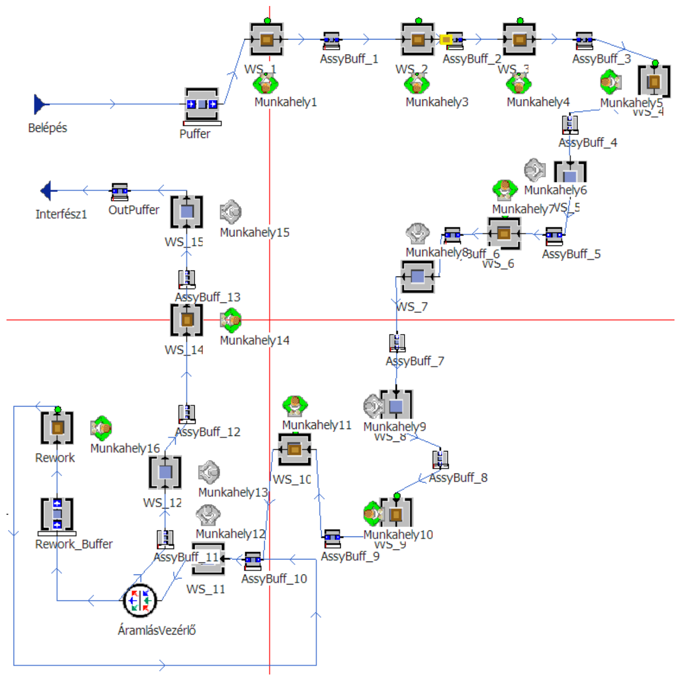

Fig. 1. Screenshot of the simulation model applied in the experiments.

rejected parts are transferred to a dedicated rework station to be corrected by a specially skilled operator. From the data processing perspective, it might be important that the shape of the line does not show any typical pattern (e.g. U-shape), as illustrated by Fig. 1.

3.2. Description of the Position Logs

As mentioned earlier, the simulation model does not only represent the physical production environment, but also replaces the real IPS by streaming the location data in real time. In order to do so, a data streaming interface (representing the IoT assets) and a data collection platform are implemented. The data streaming is performed by the DES model itself, which is able to log the location of the tracked assets in every 5 seconds (relative to simulation, can be changed arbitrarily) in JSON [9] format, including the ID of the tracked tag, its raw (unfiltered) x and y coordinates and the corresponding timestamp. Following the architecture of a real positioning system, data is streamed over a TCP/IP socket, and depending on the amount of work-in-progress (WIP), the system can generate hundreds or even thousands of logs under a minute of operation. This leads to a massive amount of data over days and weeks of operation, asking for an efficient way of capturing, storing and filtering it. For the data processing, a parsing application is implemented in *Python* that captures the streamed logs, parses the JSON entries and prepares them for permanent storage. As for the latter, a MongoDB [6] collection was used, relying on NoSQL technologies. It supports JSON as a native storage format, and enables fast and reliable load of data.

As for the nature of the data, raw position logs are typically noisy, mostly because of the dynamic operating environment. In order to simulate this phenomenon, a random noise was added to the position log stream, based on experiences from the original use case. The analyzed assembly area is cca. 15x15 meters (one line), and the workstations have a cca. 1x1 meters size. The IPS system has an accuracy of cca. 30 cm, reflected by a uniformly distributing random noise on the position data. Following a realistic case, there are some outlier values in the data, resulted by environmental changes and issues. These outliers are simulated by a larger noise on the same position data, i.e. with a combination of geometrical and uniform distributions. Accordingly, a 100 cm position error is added with uniform distribution to some datapoints determined with a geometrical distribution, where the probability of a value 0 is set to be $p=0.5$. Accordingly, this "larger" noise is added to cca. every second data sample of the stream.

3.3. Purpose of the Analysis and Questions to be Addressed

The paper is aimed at obtaining production management related metrics from the above-characterized noisy IPS logs. Applying efficient approaches to filter the noise from a large amount of streamed data, the overall objective is to calculate such metrics from the positions that can be utilized in production control and process improvement decisions. The task is to calculate assembly cycle times, production lead times and stations' workloads by using the IPS data. The cycle times are considered to be the effective amount of human labor put in performing a certain assembly operation, as the products are only staying at a workstation when they are assembled; otherwise, they stay in a buffer. In the possession of the knowledge of the actual cycle times, engineers can refine the assembly line balances and the production schedule if needed. The workloads, more specifically the utilization rates of the workstations are indirectly calculated from the cycle times, supporting production managers to derive Overall Equipment Effectiveness (OEE) related metrics.

4. Spatial Data Processing

Every IPS system has its weaknesses and usually it manifests in mispositioning, which may lead to calculating highly incorrect statistics, resulting in corrupted data to analyze. Some papers (see e.g. [10]) provide an overview of the existing wireless indoor positioning solutions and attempt to classify different techniques and systems. This section focuses on solving the problem of mispositioning by using a novel method based on noise filtration and probability theory.

4.1. Noise filtration

The first step of spatial data cleansing is the filtration of additional noise. Several effective filtering methods already exist, however, selecting the right one always depends on the problem in question [16]. A Savitzky-Golay filter [17, 14] is a digital filter that can be applied to a set of data points for the purpose of smoothing, that is, to increase the precision of the data without distorting the signal tendency. This is achieved – in a process known as convolution – by fitting successive subsets of adjacent data points with a low-degree polynomial by the method of linear least squares. When the data points are equally spaced, an analytical solution to the least-squares equations can be found, in the form of a single set of "convolution coefficients" that can be applied to all subsets of data, to give estimates of the smoothed signal, (or derivatives of the smoothed signal) at the central point of each subset. The process of S-G filtering is presented in Algorithm 1.

Algorithm 1 Savitzky-Golay filter

Given $(\tau_t, x_t)_{t=1}^{T} \in \mathbb{R} \times \mathbb{R}$ noisy spatial data
Set parameters $p, n \in \mathbb{N}$ where n must be odd
for $t \in \{\frac{n-1}{2}, \dots, T - \frac{n-1}{2}\}$ **do**
    Calculate the filtered value over the observed data $x_{t-\frac{n-1}{2}}, \dots, x_{t-1}, x_t, x_{t+1}, \dots, x_{t+\frac{n-1}{2}}$, i.e.:

$$\hat{x}_t = \sum_{s=\frac{1-n}{2}}^{\frac{n-1}{2}} C_s x_{s+t}$$

    where the convolution coefficients C_t depend on parameter p (discussed in details in [14])
end for

One of the main advantages of the S-G process is the fact that new data can be added easily and incrementally. The latter attribute enables the user to implement easily the concept even on extremely large and constantly increasing datasets.

4.2. Fit production routing on spatial datapoints

Matching the observed spatial data with a predefined routing consists of two parts: first, the smoothened data must be dragged onto the route, and then a probability-based correction is applied. Formally, the prefixed process routing is described by a directed graph G, which consists of N vertices ($v \in V$) and directed edges ($e_{ij} \in E$). The vertices of this graph are called zones, as they represent distinct workstations on the shopfloor. The exact spatial coordinates of every zone are known. For each product k, we have the filtered spatial data of movements: $\left((\tau_t^k, \boldsymbol{x}_t^k)_{t=1}^{T_k}\right)_{k=1}^{K}$ where $\boldsymbol{x}_t^k = (x_t^k, y_t^k, z_t^k) \in \mathbb{R}^3$ is a multidimensional (at most three) vector. The elements of this sequence are dragged onto graph G, simply by finding the closest vertex a_t^k by applying an arbitrary metric, e.g., Euclidean distance, i.e. finding the closest zone. By this way, another sequence $\lambda^k = (a_1^k, a_2^k, \dots, a_{T_k}^k)$ is born out of the vertices of G, where $a_t^k \in \mathbb{R} \times \mathbb{R}^3$. Let us also define $\Lambda^k = ((a_1^k, a_2^k), (a_2^k, a_3^k), \dots, (a_{T_k-1}^k, a_{T\_k}^k))$ sequence of state pairs that will be referred as steps from one zone to another.

The steps defined above are put into two categories: *true* and *false* steps. If the step (a_t^k, a_{t+1}^k) has the same start and end points (i.e., $a_t^k = a_{t+1}^k$), then the step is considered to be true. Otherwise, a certain step has to complete two conditions to become a true step. First, it has to be enabled by the prefixed routing line, i.e. the step (a_t^k, a_{t+1}^k) can be a true step if there is a directed edge in the G graph from a_t^k to a_{t+1}^k. Secondly, there must not be coming backs later, i.e. for all $r > t: a_r^k \neq a_t^k$ stands. If any of these statements are not completed for the observed step, then it is considered to be a false step. Note that – even after the noise filtration – several forbidden steps might emerge in Λ^k due to the inacuracy of IPS. This phenomenon requires some further correction.

To accomplish the probability-based correction on Λ^k, for each edge e_{ij} from v_i to v_j of graph G, we assign a p_{ij} probability, based on the frequency of good steps. The p_{ij} probabilities can be mathematically formulated as

$$p_{ij} \triangleq \frac{\sum_{k=1}^{K} \# \tilde{S}_{ij}^k}{\sum_{k=1}^{K} \# S_{ij}^k} \quad (1)$$

where # denotes the cardinality of the sets. The set S_{ij}^k contains all steps from v_i to v_j zones (vertices of G graph), i.e. $S_{ij}^k = \{(\alpha, \beta) \in \Lambda^k : (\alpha, \beta) = (v_i, v_j)\}$. The set $\tilde{S}_{ij}^k$ consists of only the true steps of Λ^k from v_i to v_j, formally, $\tilde{S}_{ij}^k = \{(\alpha, \beta) \in \Lambda^k : \forall r > ind(\beta) : a_r^k \neq v_i\}$, where $ind(\beta)$ means the lower index of element $\beta \in \Lambda^k$.

By using the above-defined p_{ij} probabilities, the λ^k sequences are updated w.r.t. the predefined routing line. We run through each λ^k and whenever we find a false step, a Bernoulli trial with probability $1 - p_{a_t^k a_{t+1}^k}$ is experimented. If the trial is successful, then all later occurrences of the starting zone must be removed from λ^k, therefore the false step is purifired into a true step. This process can be imagined as tossing a special coin. This coin says "stay" with probability $1 - p_{a_t^k a_{t+1}^k}$, or "move" with probability $p_{a_t^k a_{t+1}^k}$. When the result says "move" then we accept the jump and remove all later occurrences of a_t^k i.e. jumping back becomes impossible. However if it says "stay" then a_{t+1}^k is set to a_t^k so we do not change the state. With this method, we obtain a well defined sequence of movements. Algorithm 2 summarizes the calculation steps discussed above.

Algorithm 2 Spatial data cleansing with respect to process routing

Given $(\tau_t^k, \boldsymbol{x}_t^k)_{t=1}^{T_k}$ noisy data for all k product
Noise filtration with S-G filter which gives $(\tau_t^k, \tilde{\boldsymbol{x}}_t^k)_{t=1}^{T_k}$
Define a fixed routing line and the zone coordinates
Construct the graph representation of the routing with a fine enough directed graph $G(V, E)$
Match $(\tilde{\boldsymbol{x}}_t^k)_{t=1}^{T_k}$ points to the nearest vertices of G
Construct λ^k and Λ^k sequences
Calculate p_{ij} probabilities as above
for k in Products **do**
  for t in $1 : (T_k - 1)$ **do**
    if $a_t^k \neq a_{t+1}^k$ **then**
      if $\exists r > t : a_r^k = a_t^k$ **then**
        Delete all following occurrences of a_t^k with probability of $p \triangleq p_{a_t^k a_{t+1}^k}$
        Set $a_{t+1}^k = a_t^k$ with probability of $1 - p$
      end if
    end if
  end for
end for

We note that in real life cases, it often happens that not so many false steps occurs after noise filtration. In those cases, it might be timesaving to consider simply removing those false steps instead, if the removal does not induce a significant amount of data loss.

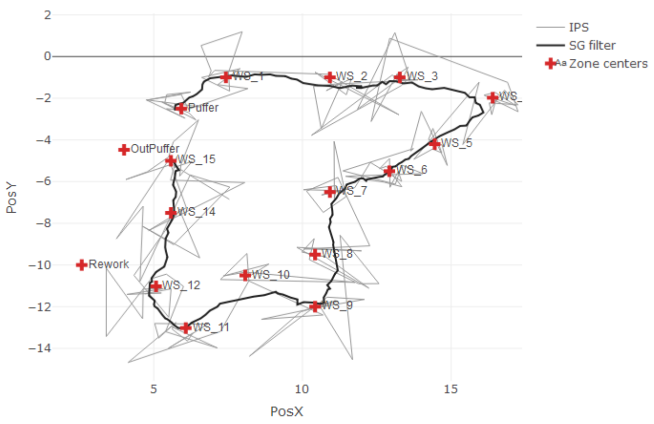

Fig. 2 Product movement before and after filtration.

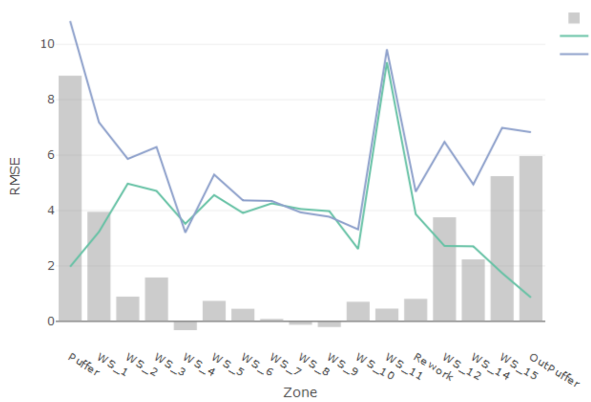

Fig. 3 RMSE of cycle times calculated with and without data cleansing and the difference between the two method (green line: cleaned data, blue line: raw data, grey bar: difference).

4.3. Evaluation

In order to assess the effectiveness of the IPS data processing method described above, here we perform an experiment by using the DES model of the assembly system, which was introduced in the previous section (Fig. 1). All calculations were performed with the statistical programming language R. The training dataset was obtained by simulating the production within one working shift, which produced cca. 47K data points in the IPS log, stored in the MongoDB database. For the sake of comparability, the true cycle times were also exported from the simulation experiments, and by nature, the idle times spent in mid-process buffers are disregarded. During the simulation run, cca. 200 products were assembled in the target area. The first step of data cleansing is the filtration of the random noise for each and every product. Fig. 2 shows the effect of applying the S-G filter (Algorithm 1) with parameters $n = 15$ and $p = 1$. It can be easily observed that without the noise filtration, the collected data might lead to corrupted cycle time calculations.

Then, the smoothened data was fitted to a predefined routing by applying lines 5-17 of Algorithm 2. In our case, the process routing is the following: Puffer (buffer) → WS_1 → WS_2 → … →WS_15 → OutPuffer (buffer). The *Rework* zone is only visited in certain cases, and it is located between WS_11 and WS_12.

A fine enough approximation of the cycle times at the workstations is of crucial importance in the scope of lead time prediction models. To analyse the accuracy of our method, we estimated the cycle times from the cleaned data and the uncleaned raw data as well. Considering the absolute error (AE), the quartiles of cleaned data's AE were closer to zero than those of the raw data's, almost everywhere. This phenomenon corresponds to our vision, according to which data cleansing develops more precise approximation of cycle time. In addition, one can observe the same event regarding to the comparison of the root mean square error (RMSE) of the two cycle time estimation (Fig. 3). At every workstation, the approximation based on cleaned data produces lower RMSE than that based on raw data, except for three stations: WS_4,

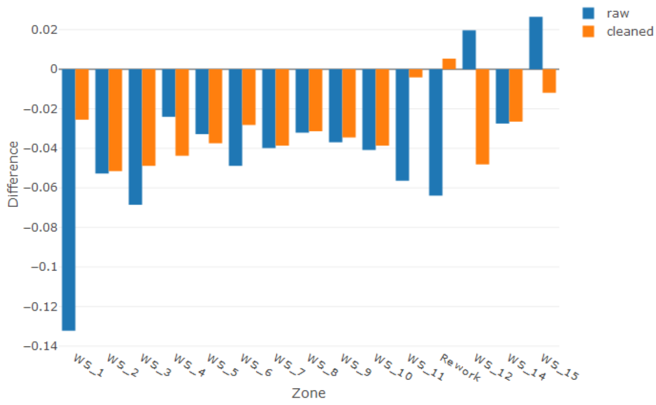

Fig. 4 Difference of the real utilization and those calculated with and without data cleansing (orange bar: cleaned data, blue bar: raw data).

WS_8 and WS_9. This anomaly can be explained by the locational structure of the assembly area.

After examining the cycle times, let us study the utilization rates of each workstation. Fig. 4 shows the differences from the actual (provided by the simulation model) utilization value. We compare two scenarios: first, utilization rates are calculated based on raw spatial data, and then the filtered and re-zoned data is used. Seemingly, the second scenario produces more appropriate approximation for almost every workstation.

5. Conclusions

Performing the numerical comparison of the IPS calculations based on raw and filtered data, let us summarize the main benefits of the above-described algorithms in production management.

5.1. Utilization of the Results in Production Management

In industrial environments, viability of advanced IoT applications is determined by the business value that they can bring. Similarly, to any IoT data analytics application, the *garbage-in-garbage-out* law holds, namely, one cannot draw the right conclusions of an analytics project, in case of unrealistic or unreliable input data is applied. In case production engineers aim at improving the processes based on the pre-calculated utilization rates and cycle times, only the realistic ones of those will provide a good starting point for the improvement. If one observes Fig. 4, significant differences can be observed in the utilization rates calculated by using filtered or non-filtered data. Similarly, if line balancing or scheduling problems are solved based on a set of parameters provided by IPS analysis, the structure of the optimal solution (e.g., a line balance) can heavily depend on the accuracy of the considered cycle times. Conclusively, it is worth to implement and apply advanced analytical methods in IPS calculations, as they provide more reliable process parameters, than those calculated from the raw location data.

5.2. Future Work

As for the future work, the authors plan to further enhance the applied methods to increase the overall accuracy of the analytics. Furthermore, a more comprehensive benchmark of filtering and smoothing algorithms is planned to be performed, with the aim of assessing their accuracy in production environments, considering various different assembly and machining shop-floor configurations.

A major part of the future work relates to the predictive analytics domain, including the prediction of manufacturing lead times, makespans of various production sequences or resource allocation rules. In this way, predictive analytics results could be integrated directly in the decision making processes, so as making a step towards the so-called *prescriptive* production management.

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