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The effect of disparities between real and simulated worlds on decision-making

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Abstract

High accuracy in information provisioning systems is often strived for by manufacturing industry, without necessarily yielding commensurate improvements in the decision-making process.
This paper explores disparities between real-world measurements and digital simulations based on a case study with soft grippers. In this research, it is demonstrated that establishing a better understanding of parameter sensitivity and highlighting the accuracy required for decisions is more relevant to the decision-making process than aiming for achievable accuracy. Consequently, this approach of seeking required accuracy requires less investments and will lead to more efficient and effective decision-making in manufacturing environments.

Keywords: Accuracy; precision; soft gripper; simulation; digital twinning

1. Introduction

Contemporary manufacturing companies frequently undergo changes in machinery, approaches, and people. This necessitates responsive decision-making processes based on volatile information provisioning. For adequate decision making, industry often overlooks that having information with appropriate accuracy is more contributive than information with the highest attainable accuracy [1]. Pursuing high accuracy requires significant investment and commitment but does not necessarily lead to better decision-making [2]. A higher accuracy of information might even complicate, stall, or limit the decision-making process. Additionally, information that appears very precise but has a lower level of trueness [1] can create a false sense of trustworthiness, leading to ill-informed decisions. This is especially the case in industry, where simulations can provide information that is used in decision making. Lengthy and complex simulations may hamper decision making, as the levels of accuracy and detail that drive the simulations may not match the accuracy actually required for adequate decision making. Especially if the simulations rely on many parameters, each with a specific (known or unknown) sensitivity and with a certain level of certainty for the value of each parameter, simulations can easily overshoot the target in supporting decision making. Instead of aiming for the highest achievable accuracy by mitigating as many disparities as possible between simulation and the real world, this paper aims to identify and apply the appropriate level of accuracy to make well-informed decisions. The treatise is related to a case study on soft grippers to define sensitivity of parameters, i.e., the effect of a parameter on the outcome, as well as their unreliability in matching simulations and reality. The case study illustrates where higher accuracy might benefit decision-making, and where lower accuracy or granularity of information suffices. The decisions mentioned in this paper concern packaging and assembly using robotics and soft

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grippers. These decisions deal with delicate and inconsistent components, but also robotic movement. For many parameters, it is often not necessary to know the exact values. Instead, depending on the (granularity of a) decision, being in the right 'ballpark' can be sufficient. For example, in the case of soft gripper material properties, dealing with a hyper-elastic material or a plastic will provide very different results in the perceived behaviour. Comparing two hyper-elastic materials will yield a more similar result. Additionally, aligning the (accuracy of) information with the decision at hand for different perspectives can help determine if the (accuracy of) information is sufficient to make the decision well-informed.

A focus on required accuracy rather than on achievable accuracy also highlights the timeliness of decisions, where decision-making processes and their execution may depend on the availability of sufficiently reliable, accurate, and crystalised information. Such an approach would facilitate industry to deploy "design by least commitment", allowing for minimal investments, while still making well-informed decisions [3, 4]. With attention shifting from decision-making workflows to the information content that enables/drives decision making, assimilating, arranging, and curating the information requires deliberate information provisioning. For this reason, this research relies on a digital twinning approach [5] where past/current data and information are accessible in a digital twin. Simultaneously, simulations, what-if scenarios, and daydreaming [6] are available in a digital prototype. Comparing between digital twin and prototype does not only allow for comparison of the real and simulated environments, but it also supports in interpretating the required accuracy to make decisions – thus straightforwardly supporting effective and efficient decision-making processes.

In the following section, disparities between real and simulated environments are discussed, followed by an elucidation of digital twinning in Section 3. Section 4 discusses the case study of this research, which aims to illustrate the effect of parameter sensitivity. In this case study, the measurements and simulations of this research are explained. Section 5 reflects on the case study and relates it to digital twinning. The concluding remarks of this research are presented in Section 6, followed by the future development in Section 7.

2. Disparities between real and simulated environments

Although industry often aims to capture and reflect all aspects of reality, it is impossible to fully achieve this. Production environments are complex due to the many relations between the elements within these environments. Additionally, the relations between the elements are dynamic and continuously change. As industry cannot keep pace with these changes, these relations, or the specifics thereof, are often unknown. This volatility of information makes it impossible to capture everything accurately. Lastly, in such complex environments, the accuracy of the data and information that is captured is only as accurate as the measurement with the lowest accuracy.

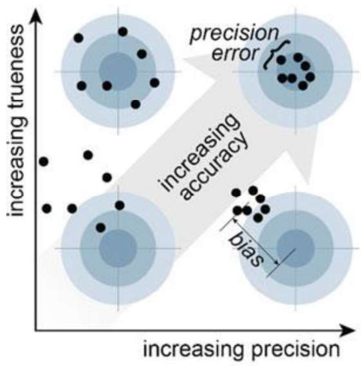

Fig. 1. Accuracy, as a product of trueness and precision [1]

2.1. Accuracy, trueness, and precision

To understand the nuances between accuracy, trueness, and precision, it is important to distinguish between these terms, as they are often used interchangeably. For this paper, the definitions from ISO 5725-1:2023 [7] are used. According to this standard, the term accuracy is described as the combination of trueness and precision. Trueness refers to the closeness of agreement between the arithmetic mean of a large number of test results and the true or accepted reference value. Precision refers to the closeness of agreement between test results obtained under stipulated conditions. Increasing accuracy is achieved by improving both precision and trueness. Fig. 1 illustrates this relation, as well as the derivatives of precision and trueness: the precision error and trueness bias. Since accuracy depends on both trueness and precision, it seems futile to focus on improving trueness if the precision is low, and vice versa. However, sufficient trueness only demands more measurements in order to be precise enough. Additionally, precision and trueness are often defined in terms of the values they aim to capture, without considering the decisions they underpin. In fact, decision-making drives the required trueness and precision, rendering both terms relative to the impact they have on the decision at hand. Where 'traditional' information systems provide information irrespective of the relative importance of information to decisions, a digital twinning approach is envisaged relates the information, its precision, and its trueness to the decision at hand [2].

2.2. Understanding disparities

In simulations, it is common practice to use approximation models to reduce complexity and therefore its computational power. Using approximations leads to less resource and time intensive simulations, at the cost of providing results that are intrinsically untrue or imprecise. Additionally, manufacturing companies often employ third-party parts, assets, and machinery for their production environments. This forces companies to work with incomplete, uncertain information about the assets they use.

Due to, amongst others, the approximations of simulations, the volatility of information, and the inherent limitations of capturing production environments, there will be a disparity between what happens in reality and the results of simulations. However, the lack of reference on trueness of different parameters, as well as the many sources, consequences, and entanglements of inaccuracies, make it impossible to define a 'truth'.

As the goal of this paper is not to define or find true values, but rather to show the relation between parameters, its disparities and the effects on decision-making, the real-world measurements will be treated as guiding, keeping in mind the aforementioned assumptions. Consequently, the simulations will use the measured values as reference point. While simulations are always intrinsically untrue, understanding the disparities between reality and simulations, and reducing simulations to what is required and what is usable, can yield better-informed decisions.

3. Digital twinning

For different stakeholders within a production environment, it can be difficult to (pre-)define what information, with what granularity, is required to make well-informed decisions. On top of that, stakeholders have different perspectives, meaning they interpret information differently based on their goals, intent, and experiences [2]. The digital twinning approach can be used to provide perspectives with the right information, at the right time, with the right accuracy, in order to make better-informed decisions. Digital twinning supports the decision-making through the purposeful development, implementation and use of digital information backbones, such as digital twins [5]. Digital twins capture the current state of a physical asset and its corresponding information, models, methods, tools, and techniques, to represent the system coherently and consistently [8-10]. Often, this current state is captured by means of sensors on a physical asset that take measurements. This data can then be complemented by e.g. engineering models to create a usable representation.

Additionally, the value of digital twinning becomes evident when it not only captures current and past states, but also helps to gain insight into possible future states. The digital twins can then form a basis to reflect on a desirable reality (should-be), as well as exploring possible alternative realities (could-be) to gain insight into the effect of decisions. These could-be states (digital prototypes) are explored through analyses and simulations, where different elements, such as parameters, can be tweaked to find consequences of change. This way, the decision-making process can be better underpinned by information. As there are endless possibilities for different parameter configurations, especially given the complex nature of production environments, the necessity for optimised and rudimentary simulations to find solutions efficiently and effectively becomes evident. As it can be assumed that digital twins are modular and recursive [2], this signifies the possibility to strive for low granularity where possible, to then increase the accuracy where required.

In order to explore "what-if" scenarios for possible future states with enough certainty to explain and underpin decisions, an understanding of the trueness and precision of a digital twin is required.

Fig. 2. Example configuration of soft grippers

As reference values for trueness are often unavailable in production environments, these values first need to be validated through measurements in order to make well-informed decisions. In this, the goal is to find the acceptable deviation in trueness and precision that still allows for well-informed decisions-making.

4. Case Study

In order to verify the effect and sensitivity of disparities between reality and simulation, a case study using soft grippers (as shown in Fig. 2) is provided. These soft grippers can be used in different configurations as manipulators for robots.
For this case study, the SG.F60S finger from SoftGripping is used for measurements, simulations, and validation. This soft gripper finger, made of a hyper-elastic silicone, functions by applying a small (0 to 0,1 MPa) pressure. This causes the fingers to expand and thus displace.

Soft grippers have gained popularity for handling food products, such as fruit and vegetables, as well as handling objects with unknown dimensions. Therefore, this paper presents a case study with soft grippers to underpin and explore the effects of different parameters characterised by limited certainty on the parameter values and sensitivity in simulations, aiming to demonstrate the acceptable deviation in trueness and precision for valuable simulations despite the lack of sufficient information on the grippers.

Soft grippers involve a significant number of known and unknown parameters, such as material properties (elasticity, hardness), geometric properties (shape, distance between gripper fingers, location, chamber volume), pressure, pressure change speed, and force. Environmental aspects, such as temperature and humidity, also influence the behaviour of the soft grippers. For this case study, the relations between parameters will be assessed for an elementary, individual soft gripper finger. Because many parameters have uncertain values (e.g. the exact material properties are not available, and the relation between finger deflection, pressure and force is deficient), parameter values are determined through a combination of external measurements and simulations.

The first part of this study consists of real-world measurements, to capture geometric accuracy and the applied force of the finger on a steel plate, at different distances. Additionally, these measurements are supplemented with the angular displacements, as presented in [11].

Fig. 3. Point cloud projected onto the 3D model

Subsequently, based on a supplied 3D model, simulations are executed, resulting in applied forces and angular displacements. These results are then compared to the real-world measurements, to identify and reflect on the disparities.

4.1. Real-world measurements

For the soft grippers, a 3D model is available. However, the internal geometry of this model is known to be unrepresentative of the actual finger. To confirm geometric correspondence for the outside, a soft gripper finger has been scanned with a Faro 3D scanner and compared to the 3D model provided.

The scanned point cloud (see Fig. 3) was benchmarked against the outside geometry of the 3D model, to validate sufficient accordance with the real finger to allow for purposeful simulations. Nevertheless, it is recognised that any geometric variation (e.g. between individual fingers) results in inherent inaccuracies in all simulations and resulting decisions.

To identify the relation between input pressure, force applied on a surface, and the distance between the finger and the surface, an experiment is set up, as shown in Fig. 4. The input pressure and distances will also be used in the simulations, allowing for comparison.

The input pressure is regulated by a pressure valve, which causes an angular displacement of the finger. This results in an applied force on a steel plate, measured by a load cell sensor. The load cell meets all requirements of accuracy class 1, as defined by ISO 7500-1 [12]. On the other hand, the nominal force of the load cell is rated for 5 N to 150 kN, while the force applied by the soft gripper finger is in the range of 0 N to 5 N. However, as mentioned, the objective of the measurements is not to find true values, but rather to have a reference for validation of the simulations. The forces were measured from an input pressure of 0 to 0,1 MPa, with increments of 0,02 MPa. Additionally, all forces were measured with distances between finger and sensor ranging from 0 to 40 mm, with increments of 5 mm. The list of components used for the force measurements can be found in Table 1.

Table 1: Experiment list of components

No.	Component	Specifications
1	Air compressor	HBM 30-liter low noise dental compressor
2	Pressure regulators	Festo VEAB-L-26-D18-Q4-V2-1R1
3	Soft gripper	Softgripping SoftActuator SG.F60S
4	Load cell sensor	Zwick Roell XforceP

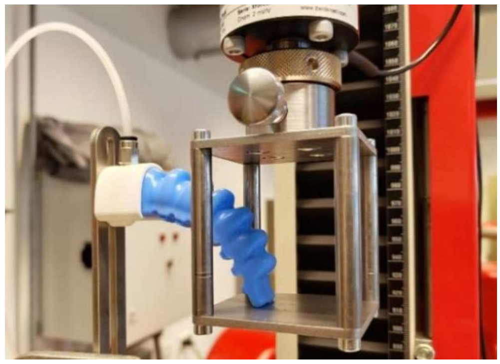

Fig. 4. Setup for force measurements

4.2. Simulations

The internal geometry, as mentioned, was known to be inaccurately modelled to the extent that the model was clearly unsuitable for simulations. As the geometry of the 3D model forms the basis of all simulations, the inner geometry was adjusted to make it suitable for application of internal pressure in the simulations. The inner geometry was approximated by stitching, shelling, and thickening the geometry based on the outer geometry. Whereas this adjusted model is now appropriate for simulations based on internal pressure, the model geometry had entities with levels of detail (e.g. small radii, sharp corners) that would cause challenges in the simulations, and more specifically in the convergence of outcomes and the speed with which these outcomes can be obtained.

The simulations are based on application of a finite element method (FEM), in which a wide variety of parameters influence the outcomes. Ranging from geometry, via material properties, to environmental influences, these parameters all come with a certain reliability and accuracy. In each case, a balance has to be struck between attainable, useful, and sufficiently accurate values for these parameters. Here, as an example, determining material models and parameters to drive FEM calculations is elaborated on.

To drive the FEM, a material model is required. Many different material models are available, all leading to outcomes with a certain inaccuracy. This can be caused by unknown model parameters, and, depending on the material model, the difference in sensitivity of these parameters. For this case study, the material is verified as a variant of silicone. Therefore, the focus for this simulation is on hyperelastic materials.

In the simulation parameters, hyperelastic models assume the material to be isotropic and incompressible, relying on a strain energy function to describe elastic energy stored in the material. Hyperelasticity serves as the fundamental basis for analytical treatment and numerical solution techniques in nonlinear continuum mechanics, neglecting phenomena like viscoelasticity and stress-softening.

Recent efforts have focused on characterizing the mechanical properties of elastomers and silicone rubbers [13-16], providing valuable insights for soft robotics applications. This characterisation has aimed to depict the hyperelastic characteristics of silicone, resulting in the proposal of various constitutive model parameters for numerical simulations using different FEM solvers [14, 15, 17, 18].

Elastomer and silicone rubbers can exhibit complex behaviour, but in the context of this research it is imperative to explore if simpler material models may be adequate for capturing the system's overall behaviour. For the simulations in this research, the Mooney-Rivlin model with two parameters was selected, due to the simplicity of capturing hyperelastic behaviour. The strain-energy function for a two-parameter Mooney-Rivlin model can be formulated as follows:

$$\Psi = \Psi(\overline{I_1}, \overline{I_2}) = C_{10}(\overline{I_1} - 3) + C_{01}(\overline{I_2} - 3) \quad (1)$$

where C_{10} and C_{01} are constant material parameters characterising the deviatoric deformation of the hyperelastic material and $\overline{I_1}$ and $\overline{I_2}$ are the first and second deviatoric strain invariants of the left Cauchy-Green deformation tensor respectively [16], which are functions of the three principal stresses. The parameter values were obtained from [17], where the hyperelastic model was fitted to experimental data. However, it should be noted that different behaviour can be expected, due to the known inaccuracies in shape and thickness of the model used in the simulation. Additionally, as the input pressure was simulated by directly applying pressure to the internal cavities for computational efficiency, the potential stiffness increases due to strain-limiting layers associated with additional materials used in the gripper's fabrication [14], as well as the stated complexity of the material behaviour. This results in larger stresses, and thus larger deformation, at various low input pressures. To compensate for these inaccuracies, the material's stiffness could be artificially increased. This compensation will lead to similar deformations under the same input pressures as observed through the measurements. Alternatively, this compensation could also be achieved by finding the correlation between real and simulated input pressure.

In addition to the material parameters, the effects of friction are also evaluated in the simulations. To assess the sensitivity of the friction conditions, two sets of simulations are performed at the various distances and pressure levels, as shown in Fig. 5. For each scenario, the reaction forces under two friction conditions are calculated: frictionless behaviour and with a coefficient of friction of 0,6.

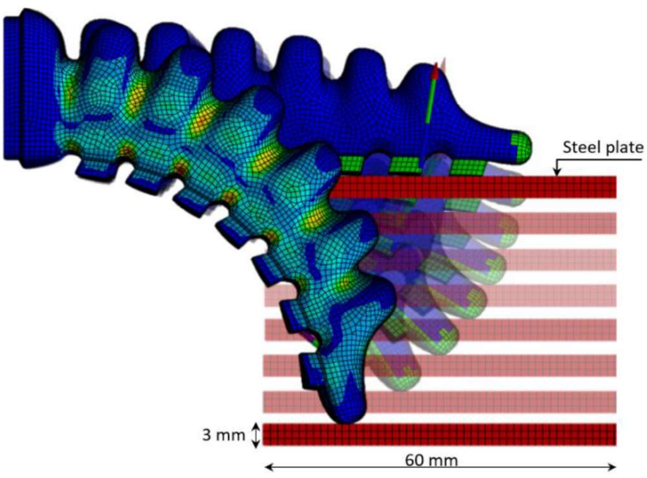

Fig. 5. Von Mises stress and reaction force at various distances

5. Validation

The forces resulting from the simulation are compared to the measurements of the experiment setup, as shown in Section 4.1. Similarly, the behaviour that results from the simulations will be compared to the measurements of [11], in order to compare the deformation. In these comparisons, rather than evaluating exact deviations, the focus was on finding trend similarities, as previously mentioned inaccuracies were inherently present, e.g. in the form of different input pressure values and output forces. Comparing the results from the experiment and the simulations to find similar trends will allow to extrapolate, where validating the extrapolations is a first step in allowing what-if scenarios, leading to e.g. redesigns of soft grippers for different applications.

Both the applied forces, as well as the deformation, showed similar trends between real and simulated worlds. Consequently, based on the experiments and simulations, as explained in Section 4, some examples on the sensitivity of parameters have been identified. For example, the material parameters have a relatively high sensitivity for the behaviour of the soft gripper finger, meaning that small deviations in these coefficients can result in a noticeable change in deformation of the finger, or even result in non-computable behaviour. Contrarily, the simulations under the two friction conditions showed minimal differences, indicating a low sensitivity for the friction parameter. Where simulations deal with a certain level of uncertainty, increasing accuracy in parameters that have detailed impact is ineffective, as long as parameters with more substantial impact have a low level of trueness. So, in this case study, it would be irrelevant to focus on increasing trueness of friction, while the deformation of the finger is not representative of reality.

For digital twinning, the purpose is to provide different perspectives (e.g., collision avoidance or grabbing delicate objects, such as fruit) with the right information, with the right accuracy, at the right time. However, for this case study, the approach used is not fitting to this purpose. Where a suitable, but highly detailed geometry is created based on a supplied 3D model as a first step for simulations, it would be more effective to start with a low-fidelity geometry. In this case study, the complexity of the geometry that comes with a more accurate 3D model has hampered the understanding of different material parameters. Instead, starting with a low accuracy approximation of the 3D model, and only increasing accuracy as it is required, would allow for more efficient, effective, and purposeful simulations.

6. Concluding remarks

In manufacturing, collecting data with pinpoint accuracy is often emphasised. Instead of dealing with the unknowns, imprecisions and inaccuracies, industry attempts to create digital infrastructures that are as accurate as possible. The downside of this is that acquiring data with a high level of detail is costly in both resources and time, while the investment does not always contribute to a better decision-making process. In fact, a high level of detail that is not required will only contribute to redundant complexity, which might hinder, limit, or even invalidate decision-making.

Additionally, it is futile to aim for the highest achievable accuracy, due to the complexity of manufacturing systems and the high volatility of its data, information, and parameter values that influence decision-making. Alternatively, defining the influence of (relations between) different parameters on the decision-making process shows to be more relevant than striving for complete and accurate digital infrastructures. In that case, the mindset shifts from attempting to achieve the highest accuracy possible to achieving the accuracy appropriate for the decision(s) at hand. Ideally, the granularity of information should match the granularity of the decision. Defining the effect of disparities of different parameters will help provide insight in where higher accuracy is required to improve the decision-making process. Based on perspective-dependent decision-making, it can become apparent what information content with which accuracy is required for well-informed decision-making. Alternatively, the available accuracy of information can dictate to what extend which perspectives can be aided in their decision-making, which leads to better underpinned decisions.

Regarding accuracy of simulations, adopting the definitions of ISO 5725-1:2023 might not be sufficient. After all, the precision of simulations is constant, as identical inputs will always yield the same results. This leads to trueness as sole factor for defining accuracy of simulations. However, as mentioned, trueness is defined by its perceived reference value, and therefore always subjective. Where the ISO standards give directions, their applicability in practice is not always guaranteed. With the approach in this paper, a new way of dealing with accuracy in decision-making comes with in reach. With that, this paper lays the foundation for decision-making that is inherently connected to digital twinning, enabling effective and efficient addressing of (un)certainties in engineering decisions. With the mindset of acquiring required accuracy, supporting the decision-making process becomes an approach by means of design by least commitment, i.e., what is the minimal accuracy that still enables well-informed decisions. This approach is especially valuable for digital twinning, as it forces to create purposeful and valuable information backbones, such as digital twins, to support the perspectives in efficient and effective decision-making.

7. Future work

The findings of this paper will be further validated in future case studies, focusing on providing required accuracy on the required level of aggregation in a digital twinning approach. These case studies will also provide insight on dealing with unknown or incomplete information. Examples of application for such case studies include the separation and sorting of empty tin cans, customised food sorting and packing, and assembly of flexible parts and/or parts with unknown dimensions.

The experiments and simulations in this paper address a basic setup with one single soft gripper finger. For subsequent case studies, these different levels of aggregation range from one finger to a configuration of multiple fingers (one hand), to multiple configurations of fingers (multiple hands/robots). In decisions across multiple levels of aggregation, it is important to keep in mind uncertainties that have the highest sensitivity, rather than attempting to eliminate all individual uncertainties, in order to best support the decision-making process.

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