Breaking down the Barriers between the Digital and the Real: Mixed Reality applied to Battery Manufacturing R&D and Training

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Abstract. In a scenario in which the manufacturing of high-performance, safe batteries on an unprecedented large scale is crucial for the energy transition and fight against climate change, research laboratories and cell production industries are facing challenges due to the lack of efficient data management and training tools. In this context, the use of intelligent devices plays an important role on the path towards the optimization of the manufacturing process and the enhancement of the battery performance while reducing production costs. In this Concept, we show how Mixed Reality technology can be used for data collection and training in real-time in battery research laboratories and pilot lines. We introduce a Mixed Reality application run on Microsoft HoloLens 2 glasses, provide a deep analysis on its ergonomic and usability aspects, and we describe how we solved the problems found during its development. Thanks to this application, users can collect data while keeping their hands free and receive advice in real time to design and build batteries with tailored properties. This optimizes data management in complex and dangerous environments, like the ones found in battery research laboratories or pilot lines. Now, thanks to our Mixed Reality application, users can collect data in the place of work, save this data automatically on a server and exploit it to receive advice and feedback to support their decision-making and learning of the manufacturing process.

1. Introduction

The ongoing global energy transition is driving an unprecedented increase in the demand for rechargeable batteries, with Lithium Ion Batteries (LIBs) emerging as the cornerstone technology. The establishment of new Gigafactories is essential to support the production scale-up required for widespread adoption of electric vehicles and renewable energy storage, and, in this scenario, the European Union, and France in particular, have taken on board the strategic importance of batteries in the energy transition and in reducing greenhouse gas emissions. In this direction, initiatives are underway to strengthen Europe's independence in the battery sector, create jobs and stimulate innovation [1]. For example, with the Battery 2030+ research initiative, Europe has put together a global roadmap to push battery research for a safer, more sustainable and more competitive future [2]. Within this framework, several critically-needed research themes have been identified, including Artificial Intelligence (AI)-driven accelerated discovery of battery interfaces and materials, and the integration of smart sensing and self-healing functionalities into the battery cells. This ambitious international initiative unfolds a comprehensive global roadmap, steering battery research toward transformative goals, and promotes the use of new technologies to stimulate and accelerate battery research and development.

The integration of intelligent digital technologies and data management tools into manufacturing and industrial processes is the main pillar of the Industry 4.0 concept, which promotes the use of new technologies such as big data analytics, blockchain and the Internet of Things (IoT), as well as Virtual Reality (VR), Augmented Reality (AR) and Mixed Reality (MR). VR, MR and AR are immersive technologies, since they create a simulated environment that the user can interact with in a way that feels real. VR is fully immersive, creates a 3D computer-generated environment and generally uses a headset, thus making it a compelling alternative for gaming and training applications [3]. On the other hand, AR allows users to keep seeing the real environment, but overlies virtual elements, and MR combines and allows real and virtual environments to coexist, with the user interacting with both of them at the same time [4]. MR offers spatial flexibility for interacting with virtual objects in real time in a more natural way, and is the only technology that frees up hands, which can be particularly useful in situations where users need to keep their hands free for other tasks [5,6]. Thanks to their unique properties, immersive technologies become outstanding alternatives for a wide range of applications, including manufacturing and assembly, where they can be used to improve the efficiency and accuracy of industrial processes with real-time guidance and assistance; customer service and sales, since they can provide customers with product information and support in real time to increase sales; or Education and training, since they can provide a more engaging and effective learning experience than traditional methods [7]. Additionally, thanks to the development of immersive devices such as MR glasses, data collection and access have become more pervasive and accessible. Interconnected computers, smart devices and intelligent machines communicate with each other and can reduce the human activity while automating and facilitating data flow management [8]. This revolution is also changing the way we work, by redefining tasks. Digitization is speeding up research, increasing efficiency and productivity, as well as quality and customization [9]. In battery cell manufacturing, integrating new technologies and artificial AI can facilitate predictive maintenance and the optimization of production processes. Overall, Industry 4.0 gives the promise to revolutionize the way battery cells are produced and used, leading to a more sustainable and efficient energy future, but several challenges still remain.

In order to seamlessly incorporate immersive technologies in battery research and production, it is essential to have a profound understanding of the battery manufacturing process. Battery cell manufacturing is a challenging and complex process, with strict safety and environmental requirements, which involves a sequence of steps [8]. The manufacturing process of LIB cells is highly sensitive to numerous process parameters, for instance to small variations in temperature, composition, pressure, humidity and other conditions that have a strong impact on the battery cell performance and lifespan, thus making it crucial to optimize them to obtain better batteries [10]. LIBs are the dominant battery technology today due to their relatively high energy density, long lifespan, low maintenance and low cost, but there is still room to improve their performance. The LIB cell manufacturing process (Figure 1) begins with the selection of the formulation and premixing of the active material, additive conductive and binder powders. Next, the liquid solvent is added to obtain a liquid, viscous ink, and, after mixing, the resulting slurry is coated on the current collector and dried in an oven to evaporate the solvent. Afterwards, the resulting electrode is calendered between two rollers that apply uniform pressure to the strip to increase the electrical conductivity by reducing its thickness and its porosity. The process must be repeated to obtain the second electrode, thus producing a LIB cell consisting of an anode (negative electrode), a separator and a cathode (positive electrode). The two electrodes are cut according to the battery cell format required and assembled using a porous separator, involving either the stacking (*e.g.* pouch cell format) or winding (cylindrical format) of the components. Next, the terminals are welded, the cell is inserted into a partially sealed capsule, and, the can is filled with electrolyte. The battery cell must be degassed before it is completely sealed. Next, the Solid Electrolyte Interphase (SEI) formation step is performed, and finally, the cell is ready to be used for its application.

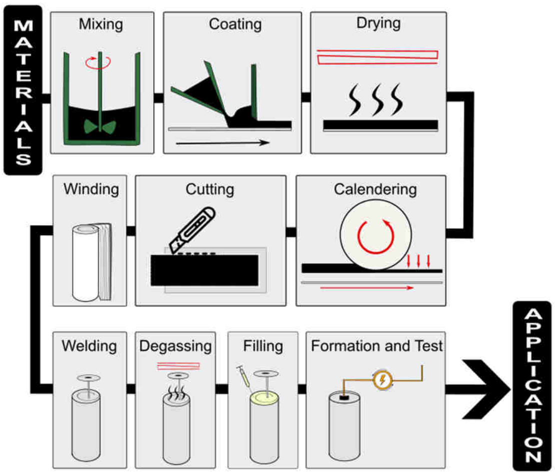


Figure 1. Scheme of the Battery Manufacturing Process. Figure adapted from Denisart et al. [11].

This manufacturing process for LIB cells is highly complex, with many interdependencies and a high degree of sensitivity to numerous parameters and a large number of different parameter combinations and work conditions [10]. Therefore, in order to accelerate research and development strategies, it is essential to create a systemic understanding to identify and understand the correlations between the different parameters (*e.g.* formulation, mixing speed, comma gap, temperature, etc.) and the electrode and cell properties (*e.g.* electrode conductivity, cell energy density). A better understanding of the manufacturing process at the mesoscale is essential, but efficient manufacturing Data Management and Training are also critical. The right Data Management policies are necessary to post-process and exploit the manufacturing data correctly, and Training is important to guarantee efficiency, productivity and data quality: the realization of both aspects through immersive technologies, as proposed by us in this Concept, arises as a promising approach to automate and accelerate battery manufacturing optimization.

Data management has been proven to be essential for accelerating research and development, and has been increasingly explored in recent years [12]. Data management is the process of collecting, storing, organizing and preserving the data created and collected by an individual, a research group or a company[13], and can be divided into three stages: quick and easy data capture, data storage and preservation, and data analysis for reuse to accelerate research. When data is poorly managed, it can be inaccurate, incomplete or inconsistent, thus making it difficult for researchers or engineers to draw meaningful conclusions from it and leading to wasted resources and time[14]. This can lead to a significant number of lost opportunities for better science and engineering. Thus, data governance and data quality have become top priorities and, for this, it is important to dispose of efficient data management processes and the right technology. When LIB cells are manufactured, a large amount of data is generated (*i.e.* input parameters such as formulation, coating speed, drying rate, calendering degree, and output parameters such as electrode porosity, cell energy density), and, therefore, it is essential to have tools that facilitate data collection and improve understanding of the data, while highlighting avenues for exploring data analysis. Several tools have already been described, although there are no common standards or policies widely accepted for data management in the battery field [15]. In this paper, we elucidate how MR tools emerge as an invaluable tool for data collection in hazardous environments during the battery manufacturing process. By seamlessly blending the physical and virtual realms, MR tools enhance safety and efficiency, providing an innovative solution for navigating and gathering crucial data in lab and industrial environments, optimizing the data management process as a whole.

Optimized data management has the potential to reduce scrap rates, improve battery quality and identify the process stages or materials that cause failures. Ultimately, this will enable a large number of still unexplored avenues of research to be explored more quickly and clearly. In this scenario, VR, AR and MR have a strong potential to optimize data collection and training. Numerous studies have examined the contribution of these technologies as training and activity support tools [16,17], with excellent results in different applications, including gaming, healthcare, training and automotive manufacturing [18].

Through our previous works which pioneered the use of VR and MR in the field of battery chemistry, we have shown that these technologies have many advantages in particular for education purposes, because they allow users to enjoy a unique immersive and interactive experience in real-time. Also, thanks to their unique characteristics, each of these technologies can be used for specific purposes. We believe that MR, in particular, has the potential to revolutionize the battery manufacturing process by improving worker training, inspection and assembly tasks. Through the use of headsets and holographic displays, workers can access data and instructions in real-time, improving efficiency and reducing the risk of error [19]. MR can also facilitate maintenance and remote assistance, allowing experts to guide and troubleshoot manufacturing processes remotely [20,21]. It has already been shown in other application contexts that MR is a suitable technology for making decisions and carrying out certain tasks, such as the design review process [22]. Finally, a study in the field of architecture shows that users seem convinced that using MR increases their personal satisfaction, particularly in collaborative situations [22].

On the other hand, the construction of several Gigafactories in Europe requires a workforce trained in many aspects such as understanding battery electrochemistry, safety protocols, quality control and production processes [23]. In recent years, training has made increasing use of digital technologies such as VR, but it is still essential to adapt training activities to the real Gigafactories' needs, to enable them to produce high-quality batteries and achieve their production targets. Especially as staff training is a continuous process, focused on real needs. The training process is highly complex and time-consuming, and must include the technical skills needed to manufacture battery cells properly (*i.e.* safe handling of chemicals and operating machinery) and understand the correlations between parameters [24]. The use of immersive technologies such as VR for professional training has become widespread in other disciplines, with demonstrated improved efficiency and quality of procedural tasks in several fields such as healthcare and automotive industry [25]–[28]. Due to total immersion, and therefore the impossibility of perceiving the outside environment, the main disadvantage of VR is that it has to be used in rooms with a large amount of space, and is therefore impossible to use in real workspaces (like a battery manufacturing pilot line or a battery factory), which might be cluttered and which are subject to strict safety regulations [11]. MR, which lets the user see both digital information and the external environment, is therefore a step forward, and offers the possibility of being assisted and trained at his/her own workstation.

The development of the final version of our solution took two years. Three generations of our MR infrastructure were developed in the context of the STARS (Smart Augmented Reality Training Assistant for Battery Scientists) and SMARTISTIC (Smart Battery Manufacturing Research and Development Assistant based on Augmented Reality Technology and powered with the ARTISTIC project) research projects, running in parallel and led by Prof. Alejandro A. Franco at Université de Picardie Jules Verne, Amiens, France. The aim of the STARS project was to build a MR software to train students, scientists, engineers and operators on the formulation and manufacturing of battery cells, while the SMARTISTIC project aimed to develop a MR software to support decision-making by scientists, engineers and battery operators when they are working on the electrode formulation and battery cell manufacturing in laboratories, pilot lines or factories. In order to maximize the usefulness and minimize user experience concerns and health impacts, we conducted extensive and rigorous ergonomic studies of these experiences.

Ergonomics is described as a "scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data, and design methods to optimize human well-being and overall system performance [29]". Ergonomics helps make human-machine interaction more intuitive by keeping the human in the center [29,30]. Ergonomics provides a batch of efficient methods to analyze the real activity of the users and highlight the needs and constraints they face during their activities. Subsequently, ergonomics allowed us to include future users in the design process of our MR infrastructure, in order to understand user scenarios, their

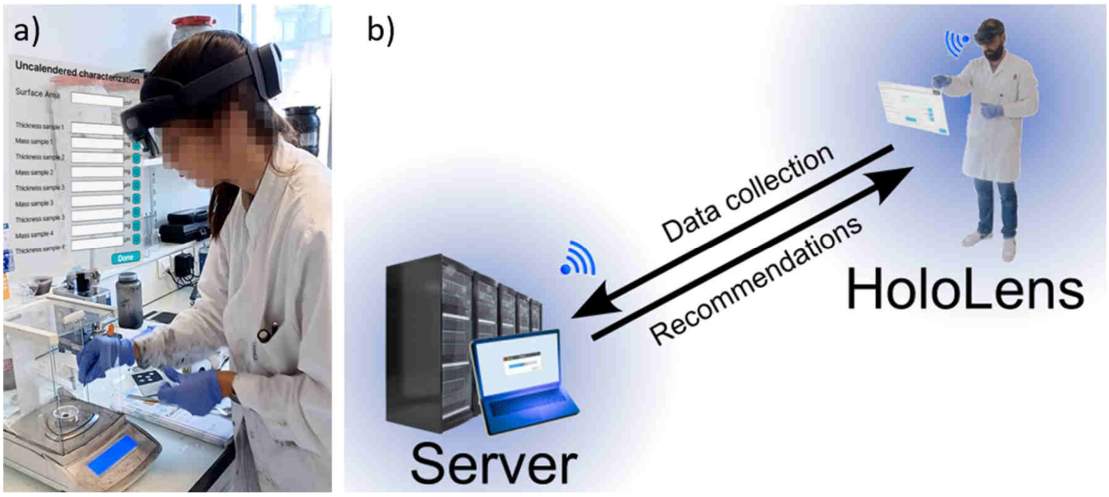


Figure 2. a) User wearing HoloLens during battery manufacturing. b) Data is collected through the HoloLens and sent to the Server for storage. The Server provides feedback to the user in the form of training or decision-making recommendations.

tasks and their working environment and then build an optimal and comfortable user experience that corresponds to their real needs [31].

In this Concept, we introduce a transformative MR application on Microsoft HoloLens 2 glasses that presents a groundbreaking solution to data collection and training challenges in the field of battery manufacturing. By enabling users to see both digital information and their external environment, our MR application fosters a hands-free approach, allowing users to collect data seamlessly and receive real-time guidance during battery design and manufacturing, and addresses the complexities of data management by automatically saving collected data on a server, overcoming the hurdles associated with dangerous workspaces. This innovative MR solution not only enhances safety and efficiency but also facilitates experiential learning in the experimental setting, marking a significant stride in advancing battery manufacturing processes. In Section 2, we describe how our MR solution was developed and tested, while the description of the application of the different developed prototypes is provided in Section 3. In Section 4 we conclude and indicate future directions for our work.

2. Method

2.1 Description of device use

The infrastructure of our MR application was adapted to assist in the training, data collection and decision-making of battery scientists, engineers and operators while they are working in electrode formulation and battery cell manufacturing in laboratories, or pilot or production lines. This innovative technology promises to improve the quality and safety of battery production, ultimately benefiting consumers and the environment, and emerges as a fascinating tool with a high potential to break down the barriers between the real and the virtual battery manufacturing worlds. It is a novel and secured software usable from MR glasses (HoloLens 2) by hand gesture. By wearing the MR glasses, the user can see holographic objects overlaid in the real environment with which he/she can interact (Figure 2a). These objects contain either instructions and advice in the form of panels or 3D objects on how to reproduce an experiment carried out by someone else or learn how to perform a manufacturing process, either a holographic notebook for data collection and providing assistance for decision-making to the user to achieve his/her desired electrode or cell properties. By simply using the MR interface and without the need for programming skills, the user can also update databases in real-time from the data she/he is acquiring from her/his ongoing experiments (*e.g.* battery electrode porosity measurement).

Our study was embarked on the development of a cutting-edge MR tool, implemented through the Unity platform, specifically tailored for Microsoft HoloLens 2 glasses. The software development phase involved coding in Unity, followed by extensive testing at user level. Noteworthy emphasis was placed on seamless integration with the HoloLens 2 platform, ensuring optimal performance and a cohesive user experience. With this application, the MR glasses were in continuous communication with a server storing the collected data and/or providing feedback to the MR user, such as recommendations on the training recipe or the manufacturing parameter values to adopt to achieve the desired electrode or cell property (Figure 2b). This raised the training and R&D efficiency because there is no need to expend time in compiling Excel-type files on computers or taking notes in hard notepads: our MR infrastructure enables engineers and lab technicians to visualize explanatory models and access to formulation guidance in real-time while running experiments in a lab or battery manufacturing pilot line.

Several ergonomic interventions were carried out as part of the projects, starting with the study of the activity of battery manufacturing to collect and analyze information about operator tasks.

2.2 Observations

Several sequences of observations were carried out to capture the actual activity of LIB manufacturing. In order to collect the most reliable data, we asked a post-doctoral researcher to manufacture a battery on the pilot line of our laboratory, and filmed all her communications, movements and tasks. We recorded this activity twice, one month apart, to identify possible variations in the conditions under which the task was performed. The data collected was used to describe and explain how the experimenters went about carrying out the tasks. In order to find out more about the sequences of the tasks, the distribution of functions between people and machines, the layout of the workplace and training needs. Each stage of the battery cell manufacturing was recorded and then analyzed with the Boris software [32].

To enrich these observations, we conducted a self-confrontation interview with the observer, asking her to provide feedback on her actions. During this interview, she explained her intentions (what she did or what she might or might not have done when she saw himself on the screen). These analyses provided us with valuable insights into the activity.

2.3 Interviews with professionals

We also supplemented our observations with interviews with battery researchers from various research laboratories and battery companies (PhD students, post-doctoral, engineers and professors, for a total of 10 hours of interviews). The interviewees were volunteers, and the interviews took place by Zoom or face-to-face in a meeting room in our laboratory. Several topics were addressed, including training needs, descriptions of activity in their organizations with different production scales, and their opinion about possible applications of MR in their activity. These interviews were an opportunity for professionals to project themselves into the future, imagine useful functionalities compatible with real needs and help generate optimal lab experiences. We aimed to provide a better user experience to guarantee satisfaction. In highly competitive sectors like the one of batteries, this satisfaction could be turned into higher sales growth, greater loyalty and a greater tendency to recommend the service [33,34].

All the interviewees' responses were transcribed and analyzed using Nvivo 11 software[35]. After analysis of the needs and constraints, a new version of the prototype was designed.

2.4 Usability testing

We tested the new version of the prototype in a real-life situation. We asked four experimentalists from our laboratory with diverse profiles (experience, gender, level of education, frequency of use of the pilot line) to make an electrode assisted by our prototype (V1). Previously, the participants filled in several questionnaires on their socio-demographic data, their tendency towards technophilia and technophobia[36] and their level of simulation sickness[37]. Each step of the HoloLens 2-assisted manufacturing process was filmed and lasted around 3 hours and 30 minutes. After use, the participants completed several questionnaires to measure cognitive load[38], level of simulation sickness (compared with pre-use score) and perception of the device[39].

3. Results

The first version (V.1) of our MR infrastructure was designed in 2021 without future users (Figure 3.a). Wearing a HoloLens 2 headset, the user had to first stand in front of a QR code in order to start using the application. The QR codes had to be strategically placed in front of each workstation (near each manufacturing process machine - mixer, coater, calender - and characterization spot - weight scale of the electrode before and after calendering, the thickness Gauges of the electrode before and after calendering) within our battery manufacturing pilot line so that the user could easily read and interact with the corresponding holographic panel (see video in Supplementary Material). Then, the headset brought up the holographic interactive panel corresponding to the associated QR code. An example of an interactive holographic panel displaying different information (slurry formulation, coating speed, calendering pressure in this case) is shown in Table 1. All the data entered by the user was automatically stored in the data server in real-time (cf. Figure 2b). Table 2 shows the variables that the user can collect at each manufacturing step with the Hololens for their storage in the database.

On this first version of our MR solution, we carried out a heuristic analysis to optimize its usability by minimizing design flaws before presenting the prototype to the first users. We used Jakob Nielsen's 10 heuristics, and Bastien and Scapin's criteria [40,41]. This enabled us to modify the positions of the buttons within the panels, and reduce the workload by eliminating certain information that was unnecessary for the user or by reducing the number of actions required for each step. Then, each panel showed the instructions to assist the user, and display input parameters for obtaining an electrode with the desired properties. To use this technology, users had to reproduce the electrode of their choice and enter the numeric data using a numeric keypad (they could not enter the wording). We asked four experimentalists (2 PhD students, 1 Engineer and 1 Researcher who had all experience in battery manufacturing in the pilot line of our lab) to use the device in real electrode manufacturing conditions and we observed a number of difficulties in terms of legibility, arm and neck pain during use, mental workload and visual fatigue. We also worked on safety to guarantee the safety of MR users in the experimental rooms when handling (dangerous) chemicals. Usually, experimenters have to wear personal protective equipment (PPE) such as a gown, gloves, goggles or a mask to avoid breathing in vapor or powders. We found out that the fixed position of the panels could be dangerous. We also fixed the QR codes so that the holographic panels were in front of the eyes and above the lab benches, but it turned out that this position was inconvenient because the user had to stretch his/her arm out in front of him/her, and dangerous because he/she was leaning over the bench and there was a risk of spilling a chemical product. This was not acceptable, so we felt that it would be better to leave users free to choose the position according to their preference and the characteristics of the situation. Furthermore, the use of MR made it easier and quicker to manufacture the electrodes, as users no longer had to search for information in their notes or laboratory notebooks or enter their data in Excel-like files on computers, as all the

	Version 1 (V.1.) 2021	**Version 2 (V.2.) 2022**	**Version 3 (V.3.) 2023**
Description	• First version of the MR application • Users can follow instructions to produce an electrode through the different manufacturing steps	• Users can collect experimental data directly in the lab. • Experimental data is transferred in real-time from the Holonens 2 to the server	• Users can manufacture an electrode and learn the process. • Users are assisted by the Hololens during the manufacturing process: they receive feedback and comments depending on the process variables used.
New features and changes	• Voice recognition function to search for recipes, *i.e.*, instructions to manufacture electrodes with tailored final properties. • Holographic panels attached to QR codes.	• Labels from previous completed steps do not show up anymore to facilitate usage. • Missing information about machine type or solvent mass is now displayed. • The position of the holographic panels follow can be set. • More attractive and user-friendly frontend.	• New training mode added to provide support and feedback in real-time. • Error messages are displayed if wrong input values are used. • The numeric keypad has been improved to make it easier to enter data. • Electrode porosity, mass loading, density and active mass are now calculated and displayed in real time.
Ergonomic problems detected	• Arm and neck pain during use. • Cognitive overload and fatigue after use. • Safety in the laboratory can be compromised due to the poor posture the user is forced to adopt. • Recurring bugs that force the user to relaunch the application. • In the case of critical bugs, the application shuts down automatically.	• The user has to relaunch the application in case of bugs. • Difficulties adjusting panels when the user enters a lot of data.	

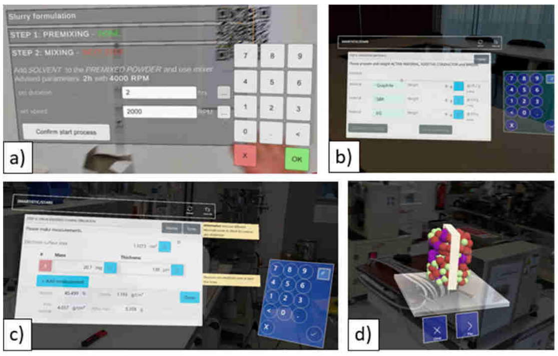
Table 1. Table describing the evolution of versions according to changes implemented and ergonomic problems identified.

necessary information and data collection functionalities were presented right in front of their eyes. We also observed that users had very positive impressions of the device after use, particularly in terms of its usefulness and attractiveness[42].

Manufacturing Step	Input Variables
Formulation	• Active material mass • Carbon additive mass • Binder mass • Solid Content
Premixing	• Machine Type • Mixing Time
Mixing	• Machine Type • Mixing Time • Solvent Mass
Coating & Drying	• Comma Gap • Coating Speed • Coating Temperature
Calendering	• Rolls Gap • Rolls Speed • Rolls Temperature • Mass of final product • Thickness of final product.

Table 2. Input parameters that can be collected through our Mixed Reality solution for the different battery electrode manufacturing steps.

In order to fix the problems detected in the first version, we designed a second version (V.2) of our MR application, based on users' feedback from usability testing and input from future users at several stages of the MR design process (Figure 3.2)). The V.2 was finalized in October 2022. V.2 was brighter and the vocabulary was adapted to the language used by experimentalists (*e.g.* weight change in mass). We have also added some missing information, such as the possibility of inputting the thickness and mass of samples to characterize the electrode after calendering. V.2. enabled data to be entered quickly and easily and stored on a dedicated server, so that it can retrieve the information from its computer in his/her office. To make data entry easier, we added a panel tracking feature to give users the option of positioning the panel where they want it and tracking it in real time. We also worked on the quality of the interface and the reactivity of the system to create a better, more memorable customer experience. We had seen from the user tests carried out in the previous version that responsiveness was an essential element, and that a lack of responsiveness could be a hindrance. We therefore tested the prototype on the prototyping line 3 times with the group's ergonomics specialist and people new to MR. After each test, we gave feedback to the developers to improve the fluidity of the device. In particular, because V.2 allowed the device to be linked to a server so this is something we wanted to improve. Thanks to the comments and experience of the experimenters involved in the projects, we were able to validate the usability and effectiveness of the system. We did not carry out user tests on this version because we wanted to test the coordination between the experiment assistant and training modes.



Add SOLVENT to the PREMIXED POWDER and use mixer
Advised parameters: 2h with 4000 RPM

Figure 3. a) V.1 of the device at mixing step, b) V.2. of the device at mixing step, c) V.3 of the device showing the training mode at the calendering step, d) V.3 of the device showing an animation of the mixing process in training mode.

V.3 of our MR infrastructure was finalized in May 2023 and combined the management of battery manufacturing data and a training functionality for this process in the same system (Figure 3.c). The manufacturing assistant has been made more intuitive. The biggest change was the addition of a tutorial mode, allowing users to learn in a real manufacturing situation by following the instructions and advice available at each stage. The tool features videos, audio and animations to help the user understand the manufacturing process and the interaction between the input parameters and the final characteristics of a battery electrode in the experimentation or pilot line room (Figure 3.d). To define the subjects and the format that might be appropriate, and to design a useful and effective training course, we drew our inspiration from the needs expressed during interviews. Indeed, professionals told us that it is essential to understand the manufacturing process before being able to apply the methods. To this end, while the trainee is making an electrode, he or she can benefit from advice on setting up the machines or on the elements to which attention must be paid. All the advice has been written by an experimentalist from our research group who regularly trains newcomers, so she has the necessary experience to identify the blocking or difficult points for trainees. The aim of this advice is to help users apply the theoretical principles during the manufacturing process. At the end of each manufacturing sequence, the user has a summary of the parameters and the formulation, and can compare them with the objectives they were supposed to achieve. Errors are therefore part of the learning process, and each difference between the objectives and what has been achieved is accompanied by advice or assistance.

Finally, depending on the user's success and errors, a subsequent training session is proposed to the user to match their needs.

4. Conclusion

In this Concept paper, we showed how MR can be beneficial in the battery manufacturing industry. Integrating MR technology into data management, decision making and training in the field of battery manufacturing can offer a significant number of benefits, including increased working efficiency due to real-time data capture, reduced errors and accelerated skills gains. In particular, our solution can be used to optimize battery prototyping processes, thanks to intuitive manufacturing and properties data collection and the ability to retrieve data effortlessly. As a complement, we are also building a computer-based tool to help users analyze the data collected by using our MR solution. Thanks to MR, battery labs and companies will be able to improve their manufacturing processes and accelerate research and development in the field, while reducing costs and guaranteeing a high-quality product. Therefore, we believe that MR is a valuable technology to support the battery manufacturing sector. In the coming months, we hope to extend the use of MR to other applications, notably other types of battery chemistries and technologies. We believe that our MR solution allows bringing digital twins, data and computer simulations directly in the place of experimentation: it can be seen then as a fantastic enabler of the removal of the frontier between the real and the digital environments, therefore maximizing the impact of digitalization in battery manufacturing.

SUPPLEMENTARY MATERIAL

We include one video as supplementary material showing the use of V.1 from an external point of view and from a user perspective.

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