

Trusted data acquisition in microelectronics manufacturing as a basis for ML-optimized processing

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Abstract

In the digitization of manufacturing processes, one of the major goals is the connection of production facilities and the use of data to digitize business processes. In order to optimize manufacturing processes and maximize the quality of the resulting product, further process information and data directly from the work piece and from the manufacturing environment are required to achieve a holistic system view in addition to the selected data that the manufacturing systems already provide. Within the SiEvEI 4.0 project, a research consortium from industry and academia works on process digitization for a manufacturing scenario where high value electronic goods are built in a distributed manufacturing environment. The key research topics addressed are the implementation of a Chain of Trust [CoT] for trustworthy distributed manufacturing and the application of artificial intelligence/machine learning to analyze and eventually optimize manufacturing processes. The basic concepts of this approach have been presented at IMAPS 2021. As an update, this paper reports on the actual experimental evaluation of these concepts in two different assembly lines, including data acquisition, data handling and AI processing with the goal to optimize processing targeting higher production yield and product quality. Specific for this work is the focus on high mix/low volume SMD assembly using fully automated equipment and Solder Ball Application.

As a result, the paper presents the experimental validation of the manufacturing process digitization and the use this digital description of a process combination to make a distributed manufacturing flow safe and increase product/process quality.

Key words

Chain of Trust, Industry 4.0, sensor networks, smart manufacturing, artificial intelligence, AI, machine learning, ML

I. INTRODUCTION

Based on the successful project PCB 4.0, where a system of wireless sensor nodes and gateways was developed to implement a variety of solutions for the digitized manufacturing, the authors have worked on a new initiative targeting a distributed manufacturing scenario for high quality and security relevant electronic components/systems. Product examples are controller modules for power plants, mobility, avionics and other applications that need a high

degree of trust in their respective environment. In a previous publication [1], the development of a concept has been presented and the basic ideas have been introduced. Here, the further detailing of this concept, the implementation into two distributed manufacturing lines and a concept validation are described.

Manufacturing scenario for such modules typically is a dedicated manufacturing site which is fully adapted to this specific system with all its technology implications. Or, alternatively and potentially more cost-effective, a distributed manufacturing approach could be chosen, that

combines the necessary expertise over more than one production site to yield a comparable result. But this implies more efforts with regard to process optimization and secure manufacturing than the conventional on-site processing. How critical security breaches in hardware manufacturing can be has been discussed in the zdnet article about counterfeit Cisco routers [2]. These were obtained through distribution channels by the US military and opened a security leak in the form of a backdoor for hackers to take control of the network system. At the same time, inferior manufacturing quality led to a fire in a government network system. In this real-life example the combination of counterfeit components and sub-standard assembly quality caused maximum damage both in the digital and in the analog world. For security-relevant devices in power distribution or in power plant applications it is clear that such "black out" scenarios caused by non-trustworthy parts or processes cannot be tolerated. This is where the idea of a chain of trust comes in, which has as its goal a known-good value chain for such sensitive assemblies. In this chain, any component - the machines, locations, firmware and the operator required for the actual product as well as for the production - should be considered in the CoT.

II. STATE OF THE ART

Manufacturing in today's digitized environment

Current manufacturing and factory environments follow the classic, pyramid-shaped model (Figure 1) with a stringent and rigid hierarchy along the value chain.

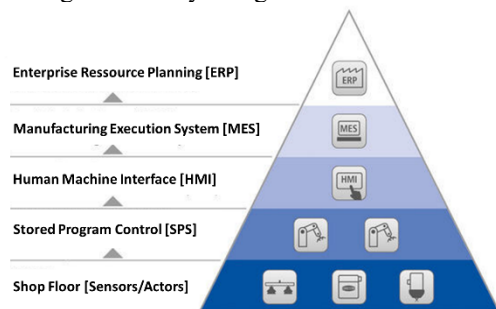


Figure 1: Representation of a classic manufacturing environment from the work level/field level to the ERP management tool. [3]

Today, the individual levels are just beginning to network with each other, but -especially in older, organically grown manufacturing environments- basically act autonomously / in isolation according to their task. Specific techniques for data transmission and processing have developed which are not compatible across these boundaries. This hierarchy has significant disadvantages in terms of flexibility and the ability to be influenced by external disturbances. One particular industry that is characterized by a rigid, throughput-optimized structure and a high degree of automation is electronics manufacturing. The production steps in these assembly processes must be processed in the

specified sequence. Furthermore, they must be carried out partly in short sequence to each other. Nevertheless, modularized, flexible manufacturing in the electronics industry is also conceivable in order to establish the described advantages of Industry 4.0 in this branch.

In electronics manufacturing, for example, highly miniaturized components are processed in high quantities in partly parallelized processes. A wide variety of data (process data, environmental data, machine status data, field data, etc.) is generated that can be relevant for the assembly process.

To optimize production processes, central (rigid) MESs are used in electronics manufacturing to control production processes and record process data. This data is typically not universally compatible and available across the described manufacturing hierarchies. But in most cases, still only the data formats of the machines of the same manufacturer are uniform. Thus, the MES must convert the data of the individual processes in order to make them available to other production processes or evaluation routines. There is even less or no compatibility and usability with regard to data synchronization along the value chain across all levels, even though first manufacturers offer integrated IOT data acquisition and processing [4]

This means that resource-efficient, flexible, distributed and secure production is not yet possible at present on a wider industrial basis and especially not for distributed and heterogeneous manufacturing sites.

Distributed Manufacturing Security Implications

In the context of distributed and networked manufacturing processes, which are connected to each other and to higher management levels via a data cloud, there is a significantly increased risk of attacks on manufacturing and industrial plants from outside via the Internet, in contrast to local plants. These new threats from hackers and professional spying devices must therefore be prevented at all levels of the automation pyramid.

An important aspect in logistics and automated production is the trustworthiness of supply and manufacturing processes. The term "Industrial Blockchain" is often mentioned in this context, that needs to be combined with a centrally organized trust authority for certificate management.

In this project a path is taken in which one or more central instances can be used to maintain trustworthiness in the signature applications for mapping transactions on a so-called Process-Record or P-record. Only authorized persons/entities can sign transactions. This CoT solution path represents an independent approach.

With regard to the development of edge computing modules [ECM], the trend is supported, which generally corresponds to the state of recent development in the direction of edge or "Fog" computing (as opposed to cloud computing).

Another trend is to install so-called microservices on edge computing modules in order to dynamically perform software updates according to the respective required and changing AI-related edge applications. The orchestration of

microservices is usually organized by a cloud instance. A sufficiently resource-efficient AI system could be deployed as a background service on a non-dedicated edge computing module, sharing its resources with other services.

Process improvement using AI

The use of machine learning in production is generally playing an increasingly important role and enables, for example, optimization of production processes [5]. In the context of this project the main challenges are the use of small- to medium-scale datasets for training, validating, and testing the AI models. In addition, real data samples for low quality products are scarce and realistic samples are difficult to obtain even in dedicated production test runs [6]. Thus, the AI evaluation in this project specifically focuses on approaches that can cope reasonably well with these challenges and provide explanations for model behavior in terms of the input data provided. In this way domain experts can be brought in to judge the trustworthiness of the trained models and to focus data collection and usage on the most relevant areas. It turns out that gradient boosting techniques stand out in this scenario [7], except for very small datasets from low volume processes, where clustering methods [8] prevail. A sustainable concept for managing the lifecycle of AI models requires new training data to be collected while the models are in production use. This allows the model to be retrained to accommodate concept drift in their data [9, 10], caused by, e.g., aging sensors or gradual changes in the production environment. Automatic continuous retraining is dangerous for critical applications, especially in conjunction with unbalanced data. The actual retraining should happen in frequent, but discrete evolutionary steps and should, again, be monitored by AI and domain experts in concert. Countermeasures to prevent the loss of previously learned knowledge in retrained models need to be applied [11, 12]. Finally, a repository of older model revisions needs to be kept so that regressions in model performance can be detected and analyzed or to reuse older revisions should their matching environmental conditions return in the future.

III. THE SiEVEI CONCEPT

Within the funded project SiEvEI a consortium consisting of various partners from industry and academia has developed a concept that adds trustability and machine learning/artificial intelligence to an existing manufacturing environment. The aim of the project is to develop a “Chain of Trust” in terms of hardware and software that establishes flexible process control for the “flexible factory” (decentralized at different manufacturing locations). The vision is, that several cooperating companies are integrated into the hierarchy, which are capable of connecting with each other in ever new ways in the sense of a cross-company Industry 4.0.

The schematic has been described before in [1] and is depicted in Figure 2.

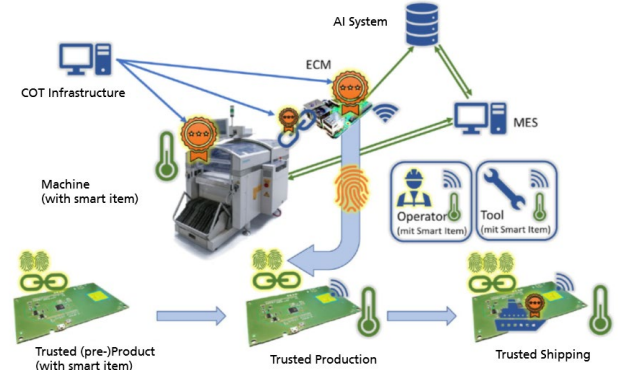


Figure 2: Illustration of a manufacturing environment with Smart Secure Item as the central element for product identification, Edge Computing Modules for information collection/preprocessing and a link to cloud services coupled by a Chain of Trust infrastructure. The CoT consists of a sequence of P-records and is linked to every product and represents the trustworthy manufacturing flow ensured by a chain of certificates.

Challenging objective of this CoT-Schematic is the integration of data flows into the existing manufacturing IT while simultaneously connecting to higher-level networks, where AI systems can be used for data processing targeting process optimization.

The aim of the AI-based evaluation is to bundle all available data into a holistic picture of the manufacturing process. In addition to the production data from the shop floor/equipment/process monitoring, data from the preceding production steps (SSI type: Smart Wireless Secure Storage Element), the environmental data (SSI type: Smart Wireless Sensor) and the users inputs (SSI type: Secure Smart Device) is collected and preprocessed by the ECMs. The ECMs then transfer the data from the shopfloor to the cloud (see Figure 3). This data is enriched with MES-information about process flow and materials and also by the respective domain knowledge of expert users. Therefore, a hybrid learning procedure is aimed at, which combines data- and model-based approaches in one procedure.

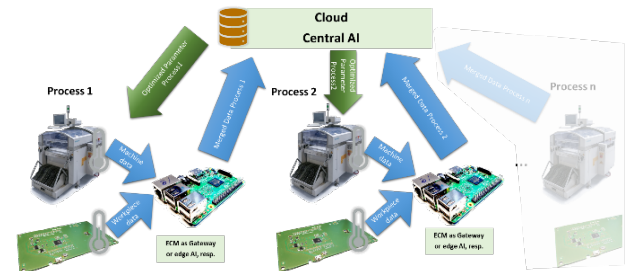


Figure 3: Concept of merging process information from various sources into the cloud and deriving process optimization potential using AI along the process chain.

IV. THE SiEvEI BUILDING BLOCKS

As described above, the SiEvEI project pursues two main goals: establishing a Chain of Trust (CoT) in a distributed manufacturing network and AI driven quality improvements based on merged sensor and process data from all previous processes and work pieces plus eventually metadata from MES and expert knowledge from users. Both goals require a specific data infrastructure for the ETL process (extract, transform and load). This infrastructure consists of the data platform, the data processing and the CoT infrastructure, all described below. In Section D the demonstration runs for data collection/processing and Chain of trust implementation will be given.

A. Data Platform

The data platform within the project is based on the ECMs collecting and distributing information from SSIs and from manufacturing equipment.

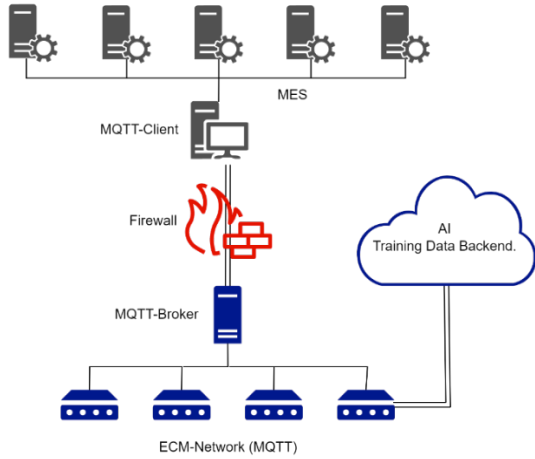


Figure 4: Integration of the ECM network into an existing production environment.

The ECMs are integrated into a dedicated subnet that is separated from the company network via a firewall. Communication in this network takes place via MQTT and the broker can either be installed on a special ECM or provided elsewhere. The automated communication of relevant process data is done via an MQTT client, which is located in the manufacturing network and has explicit access through the firewall to the ECM network.

This concept has the advantage that the production network and the ECM network are clearly separated except for a well-defined and secured interface. Such an independent network can be installed in any production facility and is independent of the individual MES. The basic structure of the network can be seen in Figure 4.

A modular firmware toolbox is available for the operation of the ECM. The structure and the essential function blocks are shown schematically in Figure 5.

The *ECM-Master-Process* is the main program that is started when the ECM is booted. It evaluates the configuration file and starts and monitors the submodules configured in it with

the corresponding parameters. The *ECM-Inter-Process-Message-Broker* is responsible for communication between the individual modules. Here, communication takes place via Unix sockets and messages can be published and subscribed to.

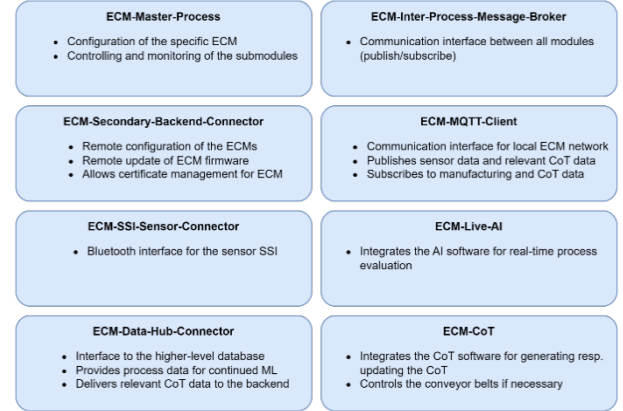


Figure 5: Modular firmware toolbox for operating ECMs

For maintenance tasks, remote configuration, updating the AI models, etc., the *ECM-Secondary-Backend-Connector* provides interfaces. Thus, the authorized ECM administrator can adjust the configuration of an ECM, update software components and renew certificates via a web application.

The *ECM-MQTT-Client* is responsible for communication in the ECM network. It connects to the MQTT broker of the local ECM network and topics can be subscribed to and published. The subscribed topics are provided internally via the *ECM-Inter-Process-Message-Broker*.

The sensor data of the SSI sensors are received by the *ECM-SSI-Sensor-Connector* and made available via the *ECM-Inter-Process-Message-Broker* and the *ECM-MQTT-Client*. The AI-supported process evaluation is integrated through the *ECM-Live-AI* module.

The *ECM-Data-Hub-Connector* collects all sensor and process data communicated in the ECM network and sends it to the backend via a websocket connection. The data is available there for further training of the AI. This data can also be referenced via a hash in the CoT. This function is implemented only once per ECM network.

The *ECM-CoT module* integrates the software for updating the CoT and controls the automated CoT process. This module has the ability to briefly stop the conveyor belts for reading and writing the CoT via a digital interface if required. The two main data sources in the manufacturing environments envisioned in the project are machines/equipment and human machine interfaces.

For most machines in the SMT production line, data can be taken from log files. These files usually are written to the local storage of the machine's computer directly after processing of each work piece is done. A file-watcher is used to trigger a software module which parses the content of the log file. The parsing is followed by conversion of numbers to their desired units and parameter names are set according

to a consent naming scheme. In the next step the data is published under an MQTT topic to a message broker. The data is also used for preparing a production record for the CoT, which is signed by the ECM's certificate and written into the embedded CoT-SSI in the work piece.

Other data sources, delivering their data directly via TCP/IP also feed into the MQTT broker. In the current project this is demonstrated for the pick& place process.

In the case of manual process steps a human-machine-interface (HMI) is used to enable user input about the current work piece. This data is structured using JSON templates, where default values can be altered or confirmed by the user and additional data can be put in. The data set is used for filling a production record for the CoT and is therefore signed by the user's certificate. It is then again pushed to the MQTT broker.

Furthermore, a number of wireless sensors (SSI) are installed throughout the shop floor. These sensors acquire environmental data such as temperature, humidity and air pressure as well as acceleration data. The data can be protected by encryption using the hardware encryption ASIC. Based on their small size they can be directly attached to a drive to check for local temperatures or mechanical abnormalities.

These SSIs broadcast their sensor data via BLE. In the SiEvEI demonstration an Edge Computing Module (ECM) receives this data. The data then is published via MQTT in the same manner as for the process data.

This makes data from all these sources available in the network by subscribing to the according MQTT topics. In the SiEvEI demonstration, this is used by software modules, running on the ECMs, to prepare CoT data records (P-record) and for the AI live inference.

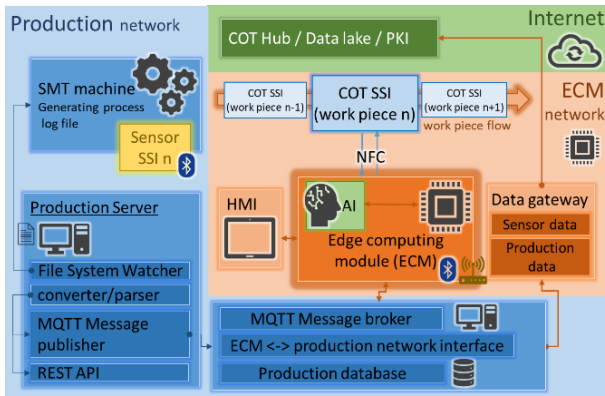


Figure 6: Communication structure within SiEvEI 4.0

In SiEvEI, an AI is trained to predict potential quality problems using training data from manual AOI verification and X-Ray verification. The training is done offline on special equipment, delivering trained models to run on the ECM. Those trained models use the MQTT subscription to load production and sensor data of the current work piece. The live inference publishes its prediction results via MQTT as well. A terminal e.g. at the X-Ray machine runs an MQTT client to show the prediction result in a dashboard on the

screen, so the operator is directly pointed to a location with a potential problem. This saves a lot of efforts to check all work pieces manually.

Especially the availability of data of all process steps for a given work piece in one place makes AI predictions much more precise.

In result the SiEvEI data infrastructure makes all data from the production and the sensors available for further use cases such as the CoT and the AI live inference (see below). Furthermore, other use cases can set up upon this data.

B. Data Processing

Deploying trained AI models to predict the quality of manufactured boards live during an ongoing production run requires a supporting software module that collects and prepares input data for those models and forwards their predictions. Figure 7 shows the most important data structures and processing steps of the AI live inference, which is running as a separate service on one of the ECMs.

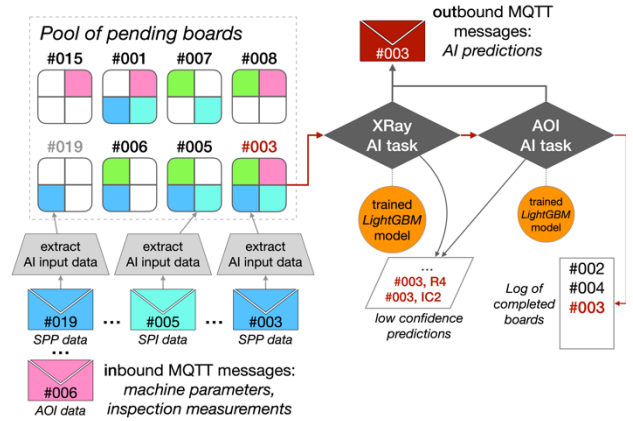


Figure 7: AI live inference processing on the ECM

The service subscribes to MQTT message topics for all relevant data sources. Internally the service maintains a pool of still incomplete input data records, where the AI inference computation is pending. Each data record in the pool relates to a specific board in the ongoing production run. Figure 7 uses just a serial number to uniquely identify each board. This identifier can be replaced with, e.g., the barcode of the board, or augmented with side and position information, as needed. An entry in the pool is created, when the first chunk of data arrives for the associated board. Further chunks of data for the same board, usually from machines in later production steps, augment the existing entry in the pool. When the entry is complete, the inference computations for the two currently implemented AI models are executed and the resulting quality predictions are combined and published under a dedicated MQTT message topic.

Optimization of the AI live inference for the ECM as an embedded target device has focused on three areas. First, from the JSON payloads of the inbound MQTT messages just the parts required as input for the AI models are extracted and stored as binary numeric values in the pool. This reduces the total memory requirements of a single pool entry from

1,233 KiB to a mere 61 KiB so that the complete pool can be simply kept in main memory. Second, the outbound MQTT messages only include the board identifier and the usually very small number of quality concerns at the component and pin level predicted by the AI tasks for that board. Finally, the size of the two AI models has been minimized, without compromising their prediction accuracy. During our AutoML exploration of resource-efficient AI methods, gradient boosting models have consistently shown the best validation and test F1-scores, as stated in Subsection D, for the available small- to medium-scale training data sets with their typical unbalanced class distributions: 1 concern per 5 training samples for the X-Ray task and 1 error per 390 samples for the AOI task. The performance of the best explored XGBoost, CatBoost, and LightGBM models was very close to each other in general, with a slight edge for LightGBM as a common method for both AI tasks. The optimized models use fewer cascaded decision trees internally and require 375 KiB for the X-Ray task and 190 KiB for the AOI task. The smaller size of the AOI model helps to reduce overfitting on the extremely unbalanced class distribution. The smaller models also reduce inference time, but at less than 10 seconds per board for both AI tasks combined this was just a welcome bonus.

Live inference during a production run needs to cope with MQTT messages being sent multiple times. This happens especially after temporary network interruptions or after parts of the communication infrastructure have been restarted. Therefore, the live inference service keeps a log of board identifiers that have already been processed completely and thus removed from the pool of pending boards. Duplicate redundant inbound messages are only problematic if they would resurrect such a completed board in the pool.

To relieve the unbalanced class distribution in the training data in the long term, the live inference also selects new data samples for training updated versions of the AI models. Beyond any of the rare defects identified during the production run, non-error samples with a low prediction confidence are collected to establish or narrow the classification boundary between error and non-error samples in newly trained AI models. This needs to be supplemented by a small share of the abundant high to medium confidence non-error samples to protect the updated AI models from catastrophic forgetting.

C. Chain of Trust Infrastructure

Last building block of the SiEvEI concept is the Chain of Trust infrastructure. The development of this chain of trust is based on an underlying 3-level public key infrastructure (PKI). A schematic of this structure is provided in Figure 8. Generically spoken, starting point is a self-signed root certificate as the PKI trust anchor.

This certificate is the most important certificate in the manufacturing chain because all lower level certificates are

signed by this one. Therefore, this certificate should be kept secret under all circumstances.

The next level includes the manufacturer certificates. All factories which are incorporated in the manufacturing process must request their own signing certificate at the root certificate authority. This is valid for various locations of one manufacturer but also for production sites of different manufacturers, i.e. Distributed Manufacturing. Using the public key of the root certificate anyone can verify the trustworthiness of a manufacturer certificate.

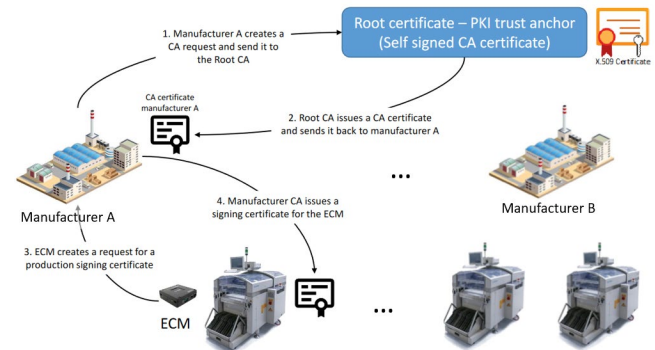


Figure 8: Chain of Trust structure applied to distributed manufacturing scenario

Finally, each manufacturer has to create a signing certificate for each machine and each manual process step which takes part in the manufacturing chain of the electronic assembly. This production related signing certificate is stored within a safe certificate container like a WIBU CmStick or in the WIBU ASIC on the different versions of the SSIs in the project.

Besides this, the public key certificate of the manufacturer as well as the root public key certificate are also stored within this container.

Going back to the chain of trust concept the different certificates are used as described in the following.

After execution of a dedicated production process step a new P-record is created containing basic information like a sequence counter value, a unique process id, a timestamp and many more.

To make the P-record trustworthy it is signed with the machine/operator specific certificate (private key) and stored as part of the CoT in the secure element of the embedded SSI inside the electronic assembly.

Additionally, the machine's public key certificate and the manufacturer's public key certificate are copied to the embedded SSI.

It is important to mention, that within the CoT single P-records cannot be deleted, modifications of a "false" entry will result in an additional P-record, which overwrites the value of a potentially faulty entry. So, any modification is documented and must be signed by a valid certificate.

Now it is possible to verify the trustworthiness of each stored P-record without accessing any external public key certificate. All necessary information can be read out directly from the electronic assembly, a valuable asset for situations

where an independent check on trustworthiness is beneficial, e.g. the last check before exchanging a security relevant control module for an avionic application.

D. SiEvEI Demonstration

Within the SiEvEI project two demonstration scenarios have been addressed, the scenario of data collection and processing at different production sites (i.e. distributed manufacturing) and the validation of the Chain of Trust concept. Both are described below.

1) ML-enhanced Manufacturing

For the distributed manufacturing scenario, the assembly of the SSI PCBAs designed by partner Sensorik Bayern was used. Topside layout and assembled SSI top and bottom side are depicted in Figure 9.

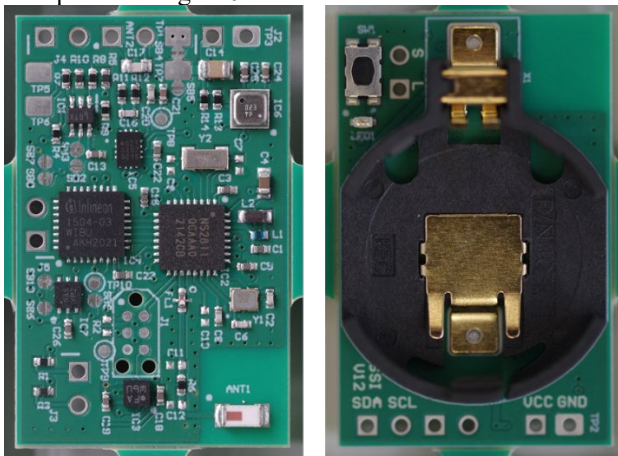


Figure 9: SSI sample images of Top and Bot layer after assembly & reflow (center and right)

The process flow for SSI manufacturing included the process steps incoming inspection - solder paste deposition - solder paste inspection - component placement - reflow soldering - final inspection. For both assembly runs a DOE was set up to provoke issues during manufacturing, to realize assembly yields well below 100 % and to generate training data for ML, that 100 % good assemblies would not deliver.

For assembly at Siemens T site the assembly processes used were related to volume manufacturing, most of the processes were fully automated, at Fraunhofer IZM site the processes related more to prototyping/low volume manufacturing, thus more manual processing was used. Both variants are shown in Figure 10.

At the laboratory SMT production line at Siemens T in Berlin the data infrastructure, as described above, was set up. During three subsequent production runs we demonstrated that the infrastructure is capable of collecting relevant information, parse and transform these sources and merge them into a data river.

As said before, Sensor-SSI were used as a test vehicle for all three production runs instead. For the first run a GEN0 Sensor-SSI with no encryption and less accuracy was used,

while for runs 2 and 3 the upgraded GEN1 Sensor-SSI were used, that have been manufactured during run 1.

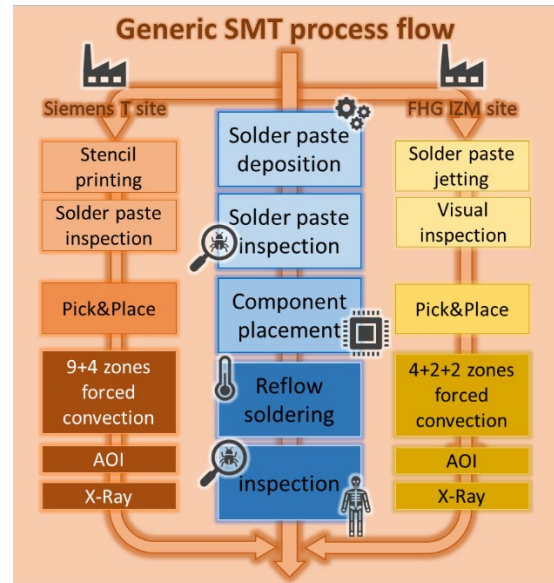


Figure 10: Process flow description for distributed manufacturing at Siemens T and Fraunhofer IZM

In order to train an AI for quality prediction, data of good and bad products are both needed. For all three runs we set up a DoE-based test plan where we pushed some of the parameters to what we believed, would be the limits and even beyond. E.g. we inserted waiting times between products to age solder paste. In the second run we did no stencil cleaning in the solder paste printing process and in the third run we even lowered the reflow temperature to barely reach the melting point.

All produced items were inspected by AOI with manual verification, underwent 100% manual X-ray inspection and were electrically tested to give a verified quality assessment to the AI training.

The first run delivered not only important training data but also 47 working SSIs out of 50 work pieces. Run 2 was equipped with sensors from run 1 and delivered 48 working SSIs out of 48 made pieces.

From run 3, with very odd process parameters we got 40 good SSIs out of 48 manufactured ones.

The data from Run 1 and 2 was used to train the AI for predicting X-ray fails and other X-ray problems. The model was transferred to an ECM and was employed in Run 3 for the live inference. The prediction of this live inference was displayed on the X-ray station upon scanning a barcode of a work piece. So, the operator was able to locate a possible problem much faster. However, for verification reason, a 100% X-ray assessment was performed anyway.

The comparison of the AI prediction and the manual inspection shows a remarkable macro-averaged accuracy of 99.28% on the test data with associated F1-scores of 0.996 for the majority class and 0.982 for the minority class. Obviously, there are still some cases, where the AI predicted

wrong. Considering the small data set of 146 pieces with only 11 fails and the fact, that training data was obtained with a different test plan this still is a promising approach.

In a second manufacturing environment, i.e. the SMD-assembly line at Fraunhofer IZM, identical products were manufactured following a different process flow. Also here, data acquisition was done to collect relevant manufacturing and quality data. The major difference is the focus of these runs on small volume manufacturing with manual data acquisition through HMI rather than automated data collection and the use of solder paste jetting instead of solder paste printing.

Data from the sources used with the small volume setup are typically entered manually into the human machine interface [HMI], data is gained via logfiles of the equipment, by readouts of equipment screens, by visual inspection of manufacturing results or by specific material analysis as e.g. solder paste analysis by an Insituware Vision system as described in [13].

The HMI is software that can display data from a CoT through a graphical interface or allow manual data entry for the creation of a P-record. MQTT is used for communication within the CoT infrastructure in both cases.

In the first case, when displaying a CoT, the HMI is subscribing to the corresponding topics of an ECM with NFC interface. When a PCBA is registered to this ECM, the CoT is read. The data is made available via MQTT and the corresponding topic. The HMI displays the individual P-records and their data, as well as the CoT validation result. This makes it possible to check both the individual entries and the entire chain.

For the second option, the HMI displays an input mask with several input fields for manual data entry. The data includes the mandatory data for the creation of the P-record as well as additional process data of interest that are to be stored. Communication via MQTT and corresponding topics is also used in this case. A process ID determines the appropriate template for data entry and the corresponding ECM. The ECM takes care of creating the P-record and entering it into the CoT after the data is received from the HMI.

Using this data input also for the small volume manufacturing various data sets have been recorded and made available to ML-analysis, where results comparable to volume manufacturing have been achieved.

2) Cross reference of distributed manufacturing

To demonstrate a decentralized production Siemens and IZM exchanged soldered boards from Batch 1 assembly and performed an AOI inspection as well as verification for them. The summary of this data on component inspection level is depicted in Table 1.

For the Siemens batch, failure rates determined were lower with both AOIs, depicting the higher quality level of fully automated manufacturing, while IZMs test setup with manual production showed a higher failure rate and thus lower yields. Both AOI inspection procedures needed a

training by the operators - the number of component NOK after first automated inspection run is unreasonably high, while after evaluation this number drops significantly. It was clear that the pseudo error rate will slightly increase since the respective inspection programs are adapted to the local production. Nevertheless, the results were comparable and the AOI can be used as quality gate independently from the boards production location.

Furthermore, the data platform is robust and flexible enough to continuously extract relevant board information. The results show that the quality procedure is stable independently from the production origin.

Table 1: AOI Result Comparison for distributed manufacturing at Siemens and IZM

Produced at	IZM	Siemens	IZM	Siemens
Tested at	IZM	IZM	Siemens	Siemens
# of PCBA	50	50	50	50
# of components	2350	2350	2350	2350
# of components - NOK before evaluation	238	316	382	236
# of components - NOK after evaluation	89	39	42	16
# of components - OK after evaluation	149	277	340	220
Component-related Yield	63%	88%	89%	93%

3) Chain of Trust demonstration

Within the SiEvEI project, the CoT demonstration was set up at the Fraunhofer IZM assembly line with the support of all partners. Prerequisites for the CoT demonstration are the availability of a manufacturing plan typically provided by an MES and an embedded SSI, which provides the workpiece with a unique ID and a storage for certificates and P-records. The reference product for CoT demonstration is a PCBA used as a driver board for a LED signal in railway applications. Into this PCBA an embedded SSI was integrated, that served as a trust anchor via embedded WIBU IC.

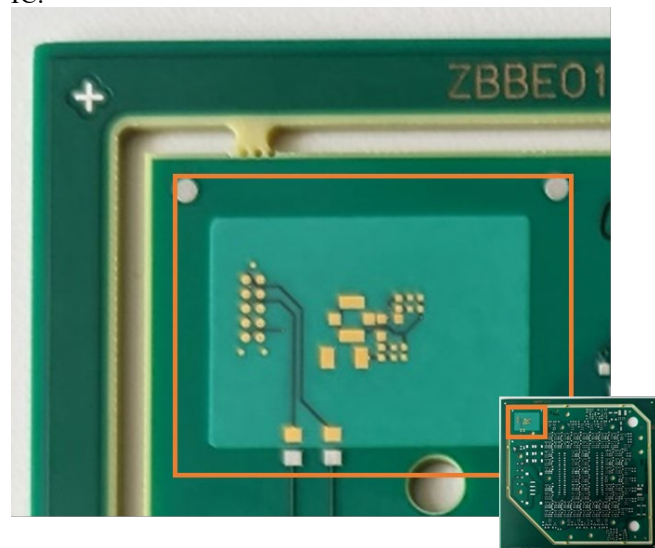


Figure 11: Reference PCBA for Chain of Trust Demonstration with embedded SSI (top left, brighter green).

The process chain used for demonstration is basically the flow depicted in Figure 10 with a certification step after each

manufacturing or analysis step. This PCB is depicted in Figure 11, with the embedded SSI in brighter green in the top-left corner of the PCB.

Just like in the later mass production for the demonstration every process step is combined with a certificate for signing the CoT. This signature is either done via ECM for automated manufacturing and via HMI for manual processing.

CoT demonstration starts with the eSSI boot sequence, where a unique ID and certificate, derived from root certificate, are generated.

Next step is the physical integration of the eSSI into the product PCB, and the combination of eSSI ID with the device ID, typically from a barcode, that is written into the memory of the eSSI and is the start of the CoT with the first P-record.

Now processing according to the process flow planned starts. For every process step, the CoT is extended with the respective P-record containing at least StepID/ProcessID and an acceptance criterion (simplest form: OK/NOK) and metadata as date and time. First manufacturing step typically is the incoming inspection of the PCB, followed by solder paste jetting, component placement, reflow and AOI analysis.

Via the linked P-records the CoT stored in the eSSI is now an integral part of the workpiece and can serve multiple purposes to ensure the trustworthiness of the electronic device after manufacturing. Due to the limitations of the lab scale demonstration, manual processes were used. However, automated CoT handling is developed in the project and preferred for later mass production and the distributed manufacturing. With additional steps the P-record can be extended to record e.g. functional testing, shipment, phases of storage and during use maintenance, test and repair steps.

Therefor an extendable naming and numbering scheme to cover all existing process steps was set up and agreed by the project partners. So all steps that might become relevant during later product lifetime can be stored on the workpiece and ensure safety/security for the workpiece and the system it contributes to.

V. CONCLUSION

Within this paper the authors presented the findings from the SiEvEI project, the concepts developed for distributed manufacturing scenarios of safety-relevant electronic assemblies. First, an infrastructure for trustworthy acquisition of manufacturing data and methods to used machine learning to improve product quality based on this data. And second, a Chain-of-Trust method that is able to ensure trustworthy manufacturing not only in one fab but also in a more complex process chain that integrates the contributions of various specialists into one product while maintaining control over the trustworthiness of the respective workpiece. Future work of the consortium will address the monitoring of process quality using ML and the possibilities to adapt test strategies to this parameter.

Acknowledgment

The authors wish to thank Elmar Guetling of atg Luther & Maelzer GmbH for his contributions to include PCB test methodologies into the CoT infrastructure. Part of this research was conducted in the project "SiEvEI 4.0" (reference number: 16ME0005), which is partly funded by the German ministry of education and research (BMBF).

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