A hybrid human-robot collaborative environment for recycling electrical and electronic equipment

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***Abstract*—In this paper, a novel hybrid human-robot recycling plant for electrical and electronic equipment is introduced. The proposed system will be developed in the context of the European research project HR-Recycler and its goal is to offer a hybrid collaboration environment for humans and robots. Through this collaboration, several currently manual, expensive, hazardous and time-consuming tasks of WEEE materials pre-processing will be substituted by automatic robotic-based procedures (categorization of electric/electronic devices, disassembling them, sorting of device components), before the materials enter the fine shredding machine. Although several solutions have been proposed for automation of recycling other types of waste (e.g. domestic), the industrial application case of WEEE recycling poses significant challenges and it is the first time, to the best of our knowledge, that a hybrid human-robot solution is proposed to address this problem.**

Keywords—human-robot collaboration, WEEE recycling

I. Introduction

The technological advances that have been achieved over the past decades have led to a tremendous increase of both the types as well as the total amount of electrical and electronic equipment that is manufactured by the industry. On the other hand, the lowering of the industrial production cost together with the continuous and rapid change in the technology (new generations of electronic products are ceaselessly introduced) have resulted in the wide spread use of the produced devices in large quantities, along with the continuous need to often being upgraded/replaced. These facts have led to the generation of enormous amounts of Waste Electrical and Electronic Equipment (WEEE).

Despite the importance of WEEE management, the industrial focus has so far been placed on more efficient methods for increasing production and lowering its cost, while the issue of the management and recycling of the generated waste has not received that increased attention. Until now, the registered practices for WEEE recycling require really expensive, extensive and time-consuming manual effort for pre-processing the input materials (categorization of electric/electronic devices, disassembling them, sorting of device components), before they are eventually introduced to a fine shredding machine and a subsequent material separation (using air/water flows, oscillating movements, magnets, etc.). This is due to the significant difficulty of the task of processing WEEE materials, compared to other types of waste (e.g. domestic), where the problem is more straightforward and automated (even robotic) solutions have already been proposed.

The aforementioned difficulty in WEEE management relates to the need for fine-grained object manipulations, elaborate device disassembly procedures and their constituent components identification/sorting. The fundamental aim of the envisaged system (and its great innovation potential) will be to replace multiple currently manual, expensive, hazardous and time-consuming tasks of WEEE materials pre-processing with correspondingly automatic robotic-based procedures (categorization of devices, disassembly, sorting of device components), before the materials are eventually provided as input to a fine shredding machine and conventional material separation steps are applied. These innovative Human Robot Collaboration (HRC) procedures pose significant challenges, relating to establishing an inherently safe and efficient collaboration environment, endorsing social cognition and adaptive behaviors to robots and incorporating Social Sciences and Humanities (SSH) elements both in the design and the validation of the proposed system.

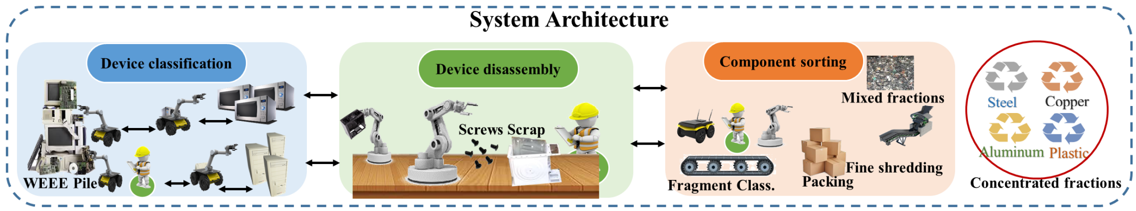

Figure 1: Flow diagram of the hybrid human-robot collaborative processes of WEEE disassembly.

HR-Recycler will ultimately target the development of a 'hybrid human-robot recycling plant for electrical and electronic equipment' operating in an indoor environment, which will integrate a hybrid collaboration environment, where humans and robots will harmoniously share and undertake at the same time different processing and manipulation tasks, targeting the industrial application case of WEEE recycling. For achieving its goals, HR-Recycler will implement highly inter-disciplinary research and development activities, which are organized in a 5-layer approach (each comprising multiple modules) that focuses on innovative technologies for factory-level modelling, cell-level perception, robotic actions and control, human-robot collaboration and smart mechatronics.

II. System Architecture

The typical non-automated procedure of WEEE recycling comprises specific steps from the time that the devices arrive at the recycling plants. The first step concerns the "Device Classification" where the electric/electronic devices are spotted, selected, categorized and transferred from the plant piles/containers/storing-packages to the appropriate workspaces for further processing. The next step involves the "Device Disassembly" which comprises the manual extraction of valuable hazardous components that may require particular treatment (e.g. capacitors, Cu coils, etc). The final step concerns the "Component Sorting" based on which manual categorization of the different types of device components and their transfer to other dedicated work cells in the recycling plant, e.g. transfer to shredding machines for further classification is performed.

Aiming towards automating this complex pipeline, we present herein the architecture of a new, collaborative hyper-mechanism that entails synergies of multiple autonomous mechatronic devices with human workers', integrated under an interconnected environment that spans the full factory floor of a WEEE recycling plant. A conceptual flow diagram of this architecture is graphically illustrated in Figure 1. Specifically, in the "Device Classification step", mechatronic systems such as Autonomous Guided Vehicles (AGVs) and human workers will collaborate in a joint and synchronized manner for undertaking the device categorization steps. AGVs equipped with robotic manipulators will perform efficient grasping and pick-and-place of heavy devices dictated by humans either by pointing or with physical human robot interaction (HRI). Once loaded, the AGVs will be capable of safe and human-aware navigation [1] substantiated through an IoT platform available on the plant that constantly delivers the robot's workspace and the human presence, towards the "Device Disassembly" work cells.

There, the mechatronic system utilized for device disassembly comprises modular and safe collaborative manipulators with adaptable grippers that allow cross-disassembly processes application. Extensive collaborative HRI among human workers and the mechatronic systems is foreseen in this step through Augmented Reality (AR) enabled communication modalities that exploit common shared information among people and machines through an intelligent assistive infrastructure.

The step of "Component sorting", is again undertaken by AGVs, which will be responsible for transporting the extracted device components or the concentrated fractions to their final collective destination within the factory floor. Given the anticipated small size of the extracted materials, the mechatronic systems consist of AGVs equipped with either conveyor belt mechatronic mechanisms or robotic hands for performing actual separation of the obtained fractions into the targeted categories.

The overall HRC environment will be centrally managed by means of factory-wide cognitive perception embraced within an advanced factory floor HRC orchestration engine. This will operate on the basis of a hierarchical factory model, whose lower level will comprise highly adaptive factory cell definitions, fusing human worker models with robot and task models, while at the upper layer, the factory floor model will be composed of interconnected adaptive cells. In this context, the explicit actions of the plant resources (AGVs, workers) can be performed with event-driven prompting mechanisms [3] that gather observations through the system's perception to synchronize the disassembly process.

The realization of such system requires a detailed modular architecture, designed on a system-centred manner for rapid development and modular engagement of the components operating in different phases. Therefore, the current system's architecture relies on ArchGen tool [4], a ROS based platform that deals with both high-level functional architecture and the low-level implementation.

III. System Building Blocks

A. *Factory-level modelling and orchestration*

In our approach, we build upon the typical definition of a work cell and we extend it. A work cell typically concerns the physical or logical arrangement of resources (people, machines, material) associated with the performance of an activity, job, or task. In an effort to extend contemporary task allocation methodologies of HRC (e.g. HRC at individual working cell level) [5], towards more advanced, integrated individual team and system level orchestration, the notion of the adaptive Collaborative Cell (**aCell**) is introduced (Figure 2):

*An **aCell** is a dynamic and adaptive element in the proposed FOF implementation that is responsible for a specific task for a given time period, with responsibilities, involved resources and overall positioning in the factory dynamically assigned and adapted in real-time, with respect* *to the overall factory workflow demands, available skills and resources.*

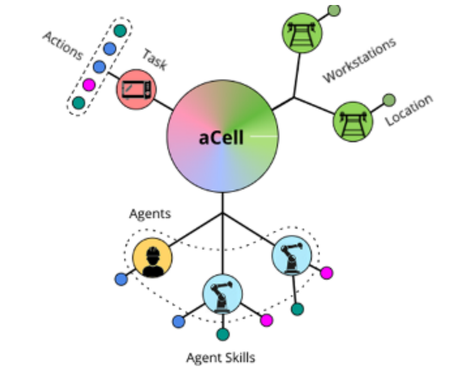

Figure 2: aCell definition.

As such, an aCell may consist in our case of a single human, factory device or robot with specific, known skills, operating as part of the overall human-robot collaborative factory team, while it may also include a human worker collaborating with the robot in its context (Figure 3). The resources, responsibilities and interconnections of each aCell to the further ones of the factory can be dynamically defined by a centralized **factory floor orchestration engine**, which is capable of overall factory floor state monitoring and real-time tasks assignment/adaptation capabilities, through cognitive perception enabled by the fusion of individual cells' perception and resources skills.

More specifically, the orchestration engine, by taking into account (a) worker and (b) robot models, along with (c) task requirements given the current factory floor state, will perform task allocation, by formulating a graph of aCells comprising robots and human workers, interconnected by assignment dependencies, spatial and temporal relationships so as to implement the current complex task (device classification, disassembly, component sorting) at hand. When deemed necessary, the orchestration engine should also drive dynamic, on the fly adaptations in the factory floor task assignments and schedule to counteract for some robot failure, process delay or significant change.

Notably, a key aim is to enhance the factory process with aCells that comprise each, a single human collaborating with several robots, aiming to extend the factory throughput per person/hour, compared to the current situation.

B. Cell-level perception methods

To equip each factory cell with advanced perception and support robot vision tasks related to the perceiving of the surrounding environment, Deep Learning architectures (e.g. Convolutional Neural Networks) will be trained to identify the different WEEE objects types as well as their constituent parts, which can be broken down into multiple pieces of highly varying size. The detection step will be realized in highly complex and cluttered environments (e.g. pile of devices), which poses additional challenges. For the CNN training we will need to generate databases of thousands of labelled images of each one of the devices to be recognized and its constituent parts.

The factory will need as well Human motion analysis and prediction, at both cell and plant level. This task involves detection and recognition of the exhibited human actions. The respective system component will rely on the use of deep 'auto-encoders' (e.g. Restricted Boltzmann Machines, sparse auto-encoders) for fusing multi-modal information (depth, 3D flow, skeleton-tracking, leap motion) and reaching robust recognition performance. Additionally, human motion analysis will be applied at multiple scales of granularity, including whole-body actions, hand gestures and finger movements. With the assumption that human motions are optimal with respect to an unknown cost function, we will use inverse optimal control (IOC) to identify the underlying motion models. These models rely on the combination of kinematic features (e.g. (angular) velocity, distance between dyad, etc.), and some physiologically motivated cost functions (e.g. energy, effort, etc.).

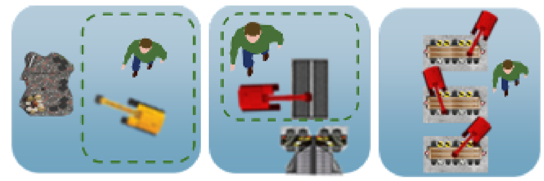

Figure 3: aCell examples.

In essence, the optimal combination of those model parameters that best describe the observed motion will be learned by IOC as the human and interaction specific personalized motion pattern. Such modelling will allow (a) identifying tasks that put high physical strain on the human worker, (b) detecting anomalies on human movement which might be used for gauging fatigues.

C. Robotic actions planning and control

A critical component of the system architecture is a unified framework for the planning and control of the manipulation tasks by the robot. The objectives are five-fold: First, a unified control policy is to be designed to regulate both the robot motion and its physical interaction with the environment. Second, the physical construction properties of unknown devices for disassembly have to be acquired by humanlike physical manipulation strategies. Third, a force-adaptive grasping strategy with tactile sensing gripper fingers for safe grasping of different components needs to be introduced. In addition, a planner that ensures secure robot operation as well as human and material safety will be developed. Last but not least, a crucial objective is to provide a lifelong mapping strategy for navigation of AGVs and facilitate holistic shop-floor decision making. We identified five key functionalities to realize these capabilities:

1) Force guided manipulation: A fundamental challenge in disassembling unknown objects are manipulation tasks with uncertain exact object dimensions and locations, e.g. the location of screws or the outer perimeter of objects are captured through camera systems, involving measurement uncertainty. The envisioned disassembly scenario requires different control strategies along the task axes and varying impedance of the controlled force depending on the structure of the object to be disassembled. Hence, a unified control policy, learned from human demonstrations, capable of regulating both the robot motion and its physical interaction with the environment needs to be constructed. The robot motion and its stiffness behaviors are modelled including the desired damping throughout the motion. The approach is suitable for generating motions that follow the same velocity profile as found in human demonstrations.

2) Construction understanding through flexible probing: The shell of modern devices is usually held together through multiple fixtures. When disassembling devices without knowing their construction plan, fixtures are easily missed – either because they are not visible, such as snap-in fixtures, or because they are not properly recognized, such as recessed screws. Therefore, we proposed an approach, where a robot opens all recognized fixtures by unscrewing all screws and cutting open the perimeter of the enclosure (Sec. III.C.1). In a second step, we mimic the behavior of humans by prying the device case along the cut opening and flexing the cut-off case. We seek to identify the location of missing fixtures through probing the case structure from multiple locations and identify possible remaining fixtures. In essence, this task necessitates using the haptic and visual modalities jointly to learn and identify object structures and construction properties. In addition, the control structures are integrated with learning algorithms to identify physical probing locations to reduce model uncertainty.

3) Versatile force-adaptive object grasping: Some components that have to be removed, need to be handled with care e.g. mercury lamps, fluorescent lamps. This requires force-adaptive grasping strategy with tactile sensing gripper fingers. Forces and torques that are applied in directions other than the ones desired for disassembly must be avoided. The first task is to evaluate suitable hardware components and develop a reliable sensor fusion method. Besides force-adaptive task-optimal gripper alignment, the gripper grasping force is the second crucial component for the success of the disassembly. For the generalization of robotic grippers, we propose a coupled feedback and feedforward controller implementation that aims at adjusting the gains of the forces applied based on sensory feedback and predictions. The controller is based on the cerebellum [6] and it can result in successful adaptive grasping, without having to implement force controllers for each object.

4) SLAM/Navigation of AGVs: The main objective of this task is to provide the AGVs of the factory floor with appropriate mapping and navigation methods. For such dynamic environments, a simultaneous localization and mapping method will be adopted in order to progressively build, maintain and update a map during the operational phase and localize to the robots within this map. AGVs are to be equipped with laser scanners and RGB-D sensors that will be utilized for the map construction, localization, obstacle detection and monitoring procedures. The interconnectivity among the existing AGVs, that are facilitated with IoT infrastructure in the shopfloor, allows them to operate in dynamic environments, thus, update the global map continuously. Considering the navigation of AGVs, both global and local navigation strategies are foreseen. Global navigation is regulated by the shop-floor orchestration engine (Sec. III.A). Local navigation is responsible for realizing the AGV's mobility and includes human aware global and local path planning techniques. Moreover, this task is responsible to address the active monitoring (Sec. III.B) by implementing the requests for maneuvering the AGVs to obtain a better viewpoint.

5) Implementing safety control in robotic planning: The goal of this task is the generation of different action policies based on a value system for safe operation. The HR-Recycler project investigates scenarios where humans and robots are jointly acting in a common workspace. To achieve safe interaction, one of the key aims of the project is to develop novel stochastic trajectory optimization and constrained policy improvement methods to enable the robot to proactively collaborate with the human partners. Additionally, the robots will pursue distinct goals derived from a unique cognitive architecture based on Distributed Adaptive Control (DAC [7]) In DAC's decision-making model, actions depend on perception, memory, valence, and goal availability. Here, we plan to expand DAC's decision-making model by incorporating a, so called, ethics engine (Sec. III.D). which modulates the valence of the decision-making model, as it constitutes a crucial component in reaching the robot's goal. The safety-control model addresses the following issues: robot safety, material safety, and human physical and perceived safety. The model is informed by the human worker model (WM) (Sec. III.E.2), the ethics engine (Sec. III.D), the proprioceptive properties of the robot, the information acquired from the environment and the outputs of the tasks defined in this section. The safety-control model includes the modulation of the speed and amplitude of the robot's movements, the speed of the conveyor belt, the distance of the robot from the human co-worker, obstacle/human avoidance as well as modulation of the speed during the transportation of the material.

D. Principles of moral actions and ethics engine

We plan to deliver an ethics engine responsible for the safe and robust operation of all the components of HR-Recycler, based on principles of human moral judgment. To ensure a suitable robot control system in collaborative schemes, we will primarily base the ethics engine on the reactive layer of the DAC architecture in which priors on morals will be defined. The ethics engine is based on an allostatic control regulation, which explicitly manages how to reach a compromised equilibrium between conflicting variables that have to be regulated. An example of conflicting variables is the compromise of robot safety, the safety of the handling material and most importantly, the safety of the human coworker. We further plan to enhance the ethics engine with a cognitive component, so that decision-making is based on context by employing the contextual layer of the DAC architecture. The ethics engine will be an inherent component of the safety control mechanism (section III.C.5).

E. Human-robot collaboration schemes

One of the key goals of HR-Recycler is to foster collaborations between humans and robots so that robots can assist them with the task at hand. Collaboration is defined as:

> "*the mutually beneficial and well-defined relationship of two or more entities to achieve a common goal*" [8].

In HRC settings, for collaboration to be efficient, the robot is required to robustly perform a given task, be trustworthy and effectively communicate with the human co-worker. Additionally, we highlight the importance of safe operation, as the robot will be required to function in close proximity to humans. To be accepted by humans as co-workers and communication partners, autonomous and transparent behaviors are essential, as they can be understood and explained [9]. Behaviors can become more easily predictable and interpretable when they use communication channels that resemble those of humans, as they provide an intuitive anthropomorphic interface [9]. Humans tend to intuitively apply the same social rules when they interact with machines or robots as when they interact with other humans [10]: they may use speech, gestures, prosodic features, emotion expression and gaze patterns to communicate. Thus, robots should not only be able to adequately “read” such communication channels employed by their human co-workers but also use similar ones.

The use of AGVs is beneficial for the project as they are suitable for efficient grasping of the electric/electronic devices, however, comparing to humanoid robots, they do have access to an anthropomorphic communication channel. We propose an interaction system (Interaction Manager – IM) based on theories drawn from human communication [11] that will deliver novel ways of interaction suitable for non-anthropomorphic robots. More specifically, we will develop a multi-level Augmented Reality (AR)-based worker-robot communication system to guide the worker via projective and optical see-through based techniques (wearable glasses). Projection-based communication will provide high priority signals that are mostly related to safety or parameters that need special and immediate attention (e.g. on robot intention). Furthermore, we will validate the theoretical approaches that affect HRI and provide socially relevant percepts and behavioral sets that allow for successful social interactions such as proactive behaviors and the motivation to interact [12].

The goal of the IM is to not only generate (when necessary) continuous interaction primitives from which communication can be bootstrapped but also, guarantee robust and personalized interactions. More specifically, information for the IM is drawn from the environment and the Worker Model (WM) which define the state space for the evaluation of and the reaction to the user. We are not aware of any non-humanoid robotic systems that are capable of effectively and centrally entrain with human behavior. We believe that the integration of social cognition and adaptive behaviors to robots in a centralized system will open the door to new HRI and HRC possibilities. The IM is central to UX, WM and learning from human input:

1) Human factors for UX analysis: explicit models of human factors that affect interaction and collaboration are necessary for the generation of behaviors according to context and human restrictions. Our aim is to identify these factors by integrating descriptors of human cognition and behavior acquired from physical and personal capabilities, ergonomics as well as emotional and cognitive perspectives (such as fatigue, distraction, workload, and trust). Using these models as a basis, we can adjust the performance degree of HRI through strategic collaborative task assignment, thereby leading to effective HRC. Within the field of human factors research, the main shortcoming of a huge number of recognition approaches that have been developed is that they assess human states at one level: either on the physical, emotional or cognitive level. So far, we are not aware of the existence of fully integrated approaches. We propose, that the combination of physical, emotional and cognitive human factors is necessary to discriminate between state patterns, enable a higher personalization, increase the situation awareness of humans and robots as well as the user acceptance, experience, and trust in the joint human-robot teamwork. We will define integrated classifiers capable to detect and discriminate a broad range of relevant human states by integrating physical, physiological, emotional and cognitive levels. More specifically, we will identify key variables (like age, gender, ethnicity, personality) that affect how users perceive the robot. On the emotional level, we will detect relevant feelings and emotions that potentially have an impact on how humans process and evaluate information such as frustration [13], the capability for sustained attention [14] or stress [15]. For the detection of human internal states, we will employ a combination of physical and physiological measurement methods (heart rate, pupil dilation, skin conductance or body temperature), video images and speech recordings. To estimate the worker’s cognitive level, we will assess critical human factors like levels of workload (cognitive tunnel) and distraction. The integration of such classifiers will enable the design and implementation of new adaptive human-robot interfaces The outcome of this section will provide valuable information for the generation of a human Worker Model (WM) and a set of robot behaviors.

2) Human Worker Model (WM) for process management and safety assurance: The WM will be used by robots when interacting with humans or when humans are present in the same physical space, to adapt the behavior of the robot to different users. Here, we will identify key variables that could potentially affect the interaction and perceived safety of the humans that include: proxemics, age, gender, ethnicity, personality, user experience and validation of user preferences acquired from the human factors. We plan to achieve user classification by the learning and acquisition of social affordances. Affective, social cues (like body posture, gesture or prosody) can signal the potential of social actions. We will extract social affordances using correlative rules. Additionally, the WM will: act as an active inference system, be used as a complementary hypothesis-testing component of the human factors for UX analysis, contribute to the factory process modeling and orchestration, and be continuously executed and updated, to include new action possibilities and ensure a robust interaction. The robot’s behavior, proximity, amplitude and speed of motion may also affect the co-worker’s perceived safety. For this reason, these parameters will be included when extracting user preferences and will be incorporated to the WM.

3) Learning from human input: HR-Recycler will be required to operate in dynamic and unstructured environments. However, it is possible that its perceptual system will not converge. To deal with uncertainty, we will implement a confidence measure that will define the certainty for its perceptions and generated actions that are to be executed. We propose that action selection is further biased by the confidence measure calculated for each of the factors. In this proactive tagging process, the robot will report its current knowledge to the human co-worker and ask them to rebalance its state-space, by either confirming its current knowledge or "injecting" to the contextual layer of the DAC architecture the appropriate information. The IM will further be enhanced to include such probing interactions.

IV. Application Cases

The proposed framework has been designed for real-world operational environments to support real user needs. As previously described, in a typical WEEE recycling plant, the process consists of the following three steps: **device classification, device disassembly and components sorting**. In the first step, a considerable amount of manual labor can be avoided by using a robot arm equipped with artificial vision to recognize each type of equipment and to transfer it to the appropriate disassembly workstation.

The second step, **device disassembly**, is highly complex and can vary significantly with the type of device. Four different types of WEEE have been selected to demonstrate the capabilities of the proposed system, which constitute the four main Use Cases.

1) Emergency lamps: the main goal is to remove the fluorescent lamps without causing any damage to it; in a possible human-robot process, the robot may recognise the type of closure and apply the necessary mechanism to open (remove the clip, unscrew, etc.).

2) Microwave ovens: the components that need to be extracted are Capacitors and Cu coil (if possible). In a human-robot collaboration scenario, the robot can move the microwave oven to an appropriate position, allow access to screws and open it.

3) PC towers: in this case, the robot can locate the PC tower to an appropriate position, allow access to screws and open the equipment, while humans can undertake the more complicated task to remove the batteries and other components.

4) Flat panel displays (FPDs): components to be extracted during the disassembly step include Hg lamps (LCDs), Cu coil (if possible), PCBs (if available). The tasks to be undertaken by a robot involve positioning of the display in the same way, possibly open the equipment, move the element to a tape or container for further processing.

The last step involves the **components sorting** procedure. Here, the components from the previous processes are separated manually, which is a highly time-consuming task. The remainings of the devices (i.e. after extracting the valuable components) typically follow a fine shredding step. In this phase, the robot can make the visual recognition of the type of material and remove it directly, depositing it in the appropriate container, while the human can assist by making sure that the materials do not accumulate, preventing every piece from being within sight and reach of the robot and observe elements that may have to be returned at the beginning.

V. Conclusions

A novel approach for hybrid human-robot collaboration in a WEEE recycling environment has been proposed for the first time in this paper. The architecture of the system and its constituent parts are described, with emphasis on the definition of eCell notion, cell-level perception, robotic actions planning and human-robot collaboration. Indicative application cases are also described, showing the applicability of the system to an industrial WEEE recycling environment. Future work involves research to advance the technology on each of the aforementioned constituent parts, in order to better address the real application needs.

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