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Context Aware Control Systems: An Engineering Applications Perspective

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ABSTRACT Cyber-physical systems revolve around context awareness, empowering objective-oriented services, products and operations based on real data. Self-aware and self-control systems are core elements in the Industry 4.0 framework towards self-sustainable adaptive manufacturing and personalized services. This development is witnessed by the context-aware pervasive assistance to users and machines in decisions making process for optimizing product performance and economic yield. While integration of the virtual and the physical world entails smart sensors communication and complex data analytics, it relies on artificial intelligence tools to manage process operations. The objective of the article is to create awareness that systems & control community must address theoretical and practical aspects from a larger perspective. Context aware control is emerging as a natural solution to maximize the use of available sensing instrumentation and the relatively low cost data logging, i.e. an important source for extracting information, interpreting and using context information and adapt its functionality to the current context of use. This article presents a concise overview of applications where context aware systems and control methodologies are relevant in the seven societal challenges acknowledged by European policy-makers: Digital Society; Food; Health and Well-Being; Smart Resource Management; Urban Planning, Mobility Dynamics and Logistics; New Energy Demand and Delivery; and Society.

INDEX TERMS Self-sustainability, global economy, intelligent manufacturing systems, self-optimization, context estimation, adaptive control, context aware control, event-based control, deep learning, random forest, iterative learning control, digital twin, cyber physical systems, societal challenges.

I. INTRODUCTION

Doubtless, the research community embraces vigorously the grand challenges envisioned in [1] with core elements from systems and control engineering. In a world where knowledge represents capacity and functionality, systems and control aspects play an essential role while emerging towards factories and machines-of-the-future along with human-in-the-loop technology. Being context-aware became an essential feature in all the knowledge-driven processes. For instance the traditional power grid is being transformed into a smart grid, which provides more secure and dependable electrical service. In fact, it is supported by two-way communication between the utility and the electricity consumer. Here, the need arises of a context-aware system for the challenges of dynamics in the network [2]–[4]. Similarly, context-aware is present in the development of the aerospace industry [5]. Meanwhile, the fourth industrial revolution (Industry 4.0) allows prediction of outcomes by the complex awareness of the process in time, thus exploiting all data, and emerging

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to an optimal solution based on advanced computing [6]. Industry 4.0 is an umbrella concept for mainstream technologies, e.g. Cyber Physical Systems (CPSs), Internet of Things (IoT), Cloud computing, Big Data analytics, Augmented Reality (AR) [7]. There have been already derived several extensions, namely Care 4.0 [8], Health 4.0 [9], Operator 4.0 [10] and others are emerging: Pharma 4.0 [11]. It only shows that automation and data exchange are critical elements to enable personalized services and adapted systems to user's preferences and context information [12].

It is important to notice that a total of 259 journals have been found by means of computerized search of the topic ''context-aware'' control. The search was performed in ISI Web of Science database and narrowed based on the selection criteria. A diagram of the steps followed to select the articles is presented in Fig.1.

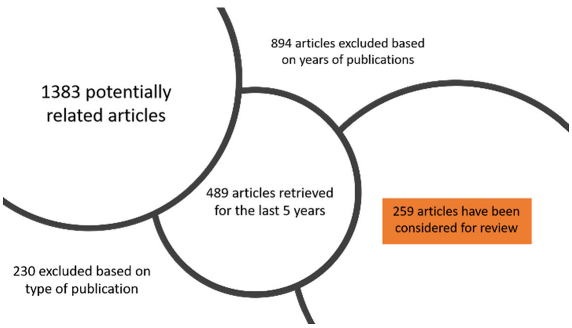

FIGURE 1. ISI Web of Science results for the search descriptor "context-aware control".

The articles resulted in this search and considered for review include the applications addressed in this article such as: Food Supply Chain, Urban Planning, New Energy Demand, Health and Well-Being, etc. When analyzing the results by publication years (for the last 5 years) an increasing trend in number of publications is observed. Hence, there is an increased interest of the research community with respect to the potential of context aware systems. An analysis of the results by the research area has been also performed and the results are shown in Fig.2.

Context-aware control systems (CACS) are proactive integrated structures that are able to action in an appropriate manner in real-time changing environment. This human-free adaptation increases usability and effectiveness by taking the monitored context into account.

A feature of CPSs is to combine context awareness, intelligent control and the use of a digital twin to consider humans as system elements and integrate them according to availability and skills [13]. CPS are characterized by the interaction between physical components with the digital world through embedded computers and networks in order to control the physical processes, based on feedback with contextual data [14]. Some examples are manufacturing plants, drone swarms, buildings with advanced HVAC controls and autonomous connected cars [15], [16]. CPSs make possible

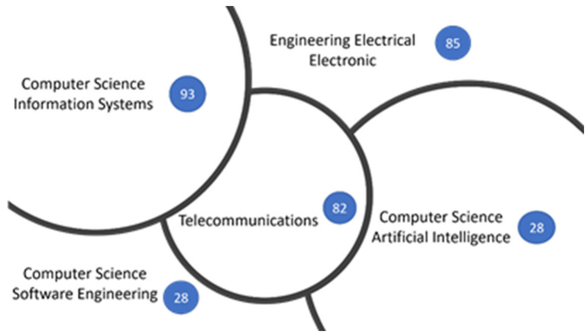

FIGURE 2. Classification of articles by the research areas, as resulted from ISI Web of Science search.

smart factories, where context-aware supports users or plants in taking decisions in real time [12], [17]. The intensive connection of software with the surrounding physical world enables CPSs to operate in different ways that can continuously change with context [7].

The main contribution of this survey is the integration of emerging control methodologies for context aware systems and cyber physical systems. The challenges enforced by the digital, heterogeneous nature of CPSs are described from the pointview of control objective planning and optimization. This article uses the classification declared at European level for thematic research areas into seven prioritized societal challenges [18], [19]. The objective of the article is to create awareness that systems & control community must address theoretical and practical aspects from a different perspective. Often, the control perspective is neglected and only the systems part is addressed, relying on lower loop control to resolve adjacent problems. However, as pointed out in this article, the control is a much needed and integrated part of the design as a global self-sustainable process.

The article is structured as follows. Notable survey articles for defining context awareness challenges and applications are summarized in the next section. Third section introduces the definitions and life cycle of context aware systems, along with suitable emerging control methodologies. This is the basis framework for the next section. The fourth section presents the context aware systems and controls classified in the seven societal challenges and referred with recent publications. A final section addresses the enabled opportunities for research.

II. PRIOR SURVEY LITERATURE

The concept of context aware systems has been reviewed and classified in the last decade, with selected notable works given in chronological order in Table 1.

While the earlier study of basic context-aware middleware and frameworks is detailed in [20], an updated survey on context-aware middleware architectures including context modeling and context reasoning is given in [25]. This survey is useful for finding the development tendency of the middleware proposals that try to overcome the challenge to provide

TABLE 1. Main surveys about context-aware systems.

Title	Reference
A survey on context-aware systems	[20]
Context-aware systems: A literature review and classification	[21]
Context-aware service engineering: A survey	[22]
Context-aware adaptive and personalized mobile learning systems	[23]
Context awareness in mobile computing: A review	[24]
Context aware middleware architectures: Survey and challenges	[25]
Engineering context-aware systems and applications: A survey	[26]
A survey on context-aware ubiquitous learning systems	[27]
Context-aware computing for mobile crowd sensing: A survey	[28]
The Modeling, Organization, Middleware (MOM) of context-aware systems: A survey	[29]

an efficient solution for an increased usability of context. Technical considerations for context aware middleware and different architectures were analyzed and compared, revealing that there is no context aware middleware architecture suitable for all settings.

From the viewpoint of smart learning environments for CAS, mobile learning environment systems and approaches are discussed in [23] based on two main issues in designing adaptive and personalized mobile learning CAS. These are the learner's contextual information and the type of adaptations made available by the previous information. Similar, context awareness in mobile computing is reviewed in [24], including basic design principles and security issues in context-aware mobile computing. Moreover, data sharing within a population has offering the opportunity for mobile crowd sensing, that is surveyed in [28] from three viewpoints of concepts, context-awareness, and functionalities. These are the main steps for specifying a computer systems, going from general specifications to context-awareness related non-functional requirements and finally to functional ones. Finally, the survey includes discussion on the results obtained and future directions of research. In addition, shifting from mobile learning to its expansion, a more recent overview of context-aware ubiquitous learning environment systems and approaches is presented by [27]. During the rapid development of ubiquitous computing, this survey is mainly concerned with ubiquitous learning because it is the intelligent learning environment achieved by context-awareness. Beside presentation of smart learning environments, the research challenges and future research directions are described.

A classification framework is given in [21] and categorizes CASs in terms of a five-layering architecture: concept and research layer, network layer, middleware layer, application layer and user infrastructure layer. By contrast, another classification for context-aware methodologies and solutions is suggested in [22], but the focus is on the most appropriate context management categories for service engineering. Centering on the benefits brought by the decoupling of the service logic from the context handling layer, three approaches have been considered as solutions: source code level handling, model-based and message interception.

The analysis of context concepts and CAS's features is included in a more generalized survey in [26], addressing the main challenges and possible research directions. The demands of CAS techniques are highlighted for the most common stages of a development process: requirements elicitation, analysis & design, implementation and deployment and maintenance. Therefore, the unification of different techniques from literature into methodologies that can be used for CAS development is further done by assessing experts opinion and needs through a questionnaire. The literature review shows the difference in methodologies from the conventional development, with the focus on better fitting of the needs of both CAS creation and community.

Finally, a literature analysis featuring the basic CAS components (modelling, organization and middleware) is summarized in [29]. Various context-aware ecosystems and middleware from the literature are discussed with focus on the function of the aforementioned building components. Such that, the contribution of the latter survey supports the knowledge needed by a newcomer of the basic components required and essential to develop and implement a robust CAS. However, from the above referenced list, containing recent surveys of context aware system operation, the control related problems are neglected. We will address this issue in section IV.

III. CONTEXT-AWARENESS

Several definitions of context are provided in the ubiquitous computing literature [14]. Closer definitions to the operational aspect of a dynamic process are presenting the context as a changing execution environment or as physical and conceptual states of interest for an entity. Interactive systems as CASs require different modalities of communication between different components, including the human-in-the-loop element. An autonomous self-aware system is reducing the workload of the users, allowing them to focus their attention on high level critical decision policies. The final decision maker for the system's action is the user operating in different situations, after the context estimation updates provided by the CAS.

Context awareness is characterized by fundamental capabilities of sensing context information (including processing) and presenting them to the general decision making element. The key of a CAS consists on presenting only the contextual information in the form needed by the application, without the details of the sensing system [30]. The operation of CA systems requires four main steps for context information management [31], as presented in Fig. 3. More information about of each step for context information management is presented in appendix.

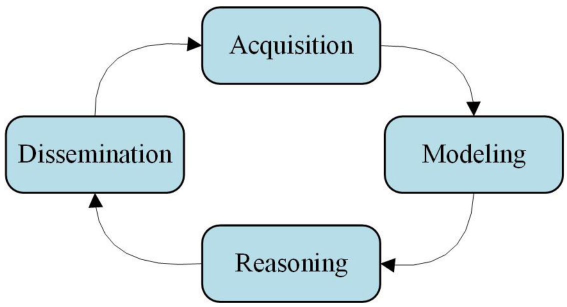

FIGURE 3. Life-cycle of context-aware systems.

Nowadays, context awareness is integrated in CPSs that pervade diverse sectors of the physical world. CAS impact applications where context-based adaptation of tasks and decisions are highly required [20]. This feedback is provided by adequately testing and/or sensing the environment. Overall, every context-aware application is developed for addressing three fundamental components: i) context acquisition (using sensors for collecting low-level contextual information); ii) processing (applying reasoning methods for obtaining high-level contextual information); iii) acting (automatic execution of services and actions after context detection) [32]. To summarize, insight into the context of operation brings added value for self-adaptation and self-optimization. A conceptual view is given in Fig. 4. As observed earlier, the control specific adaptation is intrinsic in the global operation of the process. Notice the flow of information is still uni-directional, as with classical operations approach. Ideally, the information flow would be horizontal/vertical throughout all levels of the process. Later on in this article, we propose such an architecture.

IV. RELEVANT CONTEXT AWARE CONTROL METHODOLOGIES

The awareness feature of CPS systems can be exploited to create dedicated decision making strategies, relevant for the present context. There are several control methodologies which appear as natural solutions to the management of CASs. Pairing a context aware solution with a CAS system creates a Context Aware Control Systems, denoted further by the CACS abbreviation. These type of systems have intrinsic features that resonate with contextual paradigms. This section brings forward most notable articles and reviews with highly relevant control methodologies. The concept of context aware control strategy is illustrated in Fig.5. The context awareness core element of the methodology involves a mapping of the dynamic CPS system in various conditions. This can be apriori calculated/estimated/inferred for different objectives, which may be enabled depending on the current situation of the process and its environmental/operating conditions.

In a CACS methodology one may distinguish three phases described hereafter.

Phase 1: For each objective (e.g. safety, maintenance, nominal, high throughput operations) a context map is calculated. This takes into account the manipulated and controlled variables and can be done from regression data. As a result, a set of distribution of pairs of input/output variables is obtained. Some of them deliver good performance for that specific objective (i.e. green bullets) and some other less (e.g. orange bullets). Other are to be avoided (e.g. red bullets). The result is a database of maps for different envisaged objectives.

Phase 2: Once these maps are available, the process is evaluated online with visual feedback information. The analysis of the visual feedback will identify events which will have as a result an output moving from green bullet area to a lower performance are or forbidden zone. If this is detected, then the event-based controller/formalism is activated.

Phase 3: For each context map and objective, a set of controller parameters are apriori available (e.g. updated from prior data). Once a trigger comes from Phase 2, the context is evaluated and the objective is prioritized to perform the best next thing in order to bring the process back to green bullet operation.

Example: if an instrumentation failure is present, the green bullet is no longer achievable, and the context map to be further used for decision-making process should be the one for safety or for maintenance operation conditions.

We summarize hereafter the control strategies in decreasing order of their current utility and relevance.

The control strategies with reasoning closer to context aware systems are the **iterative learning control (ILC)** [33] and **reinforcement learning (RL)** [34], both based on learning from repetition to repetition or self-taught without intervention from an expert control engineer. For instance, a data-driven CPS control problem of with communication faults on multiple channels is presented in [35]. To resolve it, a watermark-based anomaly detector and a learning-based switched control policy are proposed. Under this cooperation the reliability of the systems under the faults was guaranteed. As with all CPSs, data feedback especially big data, are at the core features, demanding suitable filtering techniques for extracting new, useful, learning-worth information from the environment. Both methods use a reward system to penalize or augment the value of actions in the decision making process. Of special interest are those systems demanding optimal control in presence of nonlinear, possibly stochastic dynamics with high level of uncertainty. While their relevance to CACS for CPSs is unarguable, the stability of such control strategies remains much of an open question.

Event-based control is an emerging control algorithm designed to take action at irregular, independent times during the operation of the process [36]. In this approach, the controller is apriori defined or onset tuned to fulfill a preset goal. The controller can be a switching function between apriori calculated controller parameters. These controller settings are apriori computed based on various predefined

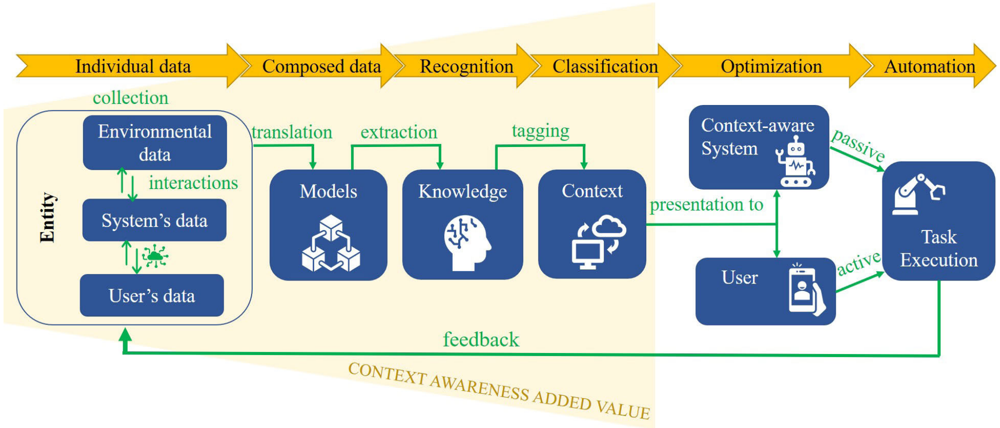

FIGURE 4. Schematic representation of context-aware systems operation mode.

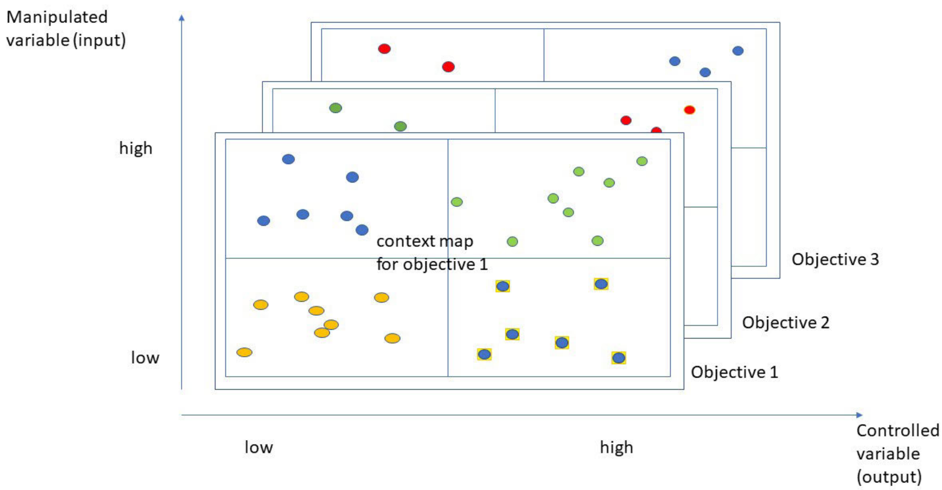

FIGURE 5. Illustrative concept of context aware control system with prioritized multi-objective optimization.

contexts - this reduces significantly the real time computational costs making it a viable solution for fast acting systems [37]. An application based on event-triggered robust tracking control method for a one degree of freedom (DOF) link manipulator is given in [38]. This method is in the form of discrete-time, and only uses the sampled-data position signal, thereby being more suitable for practical applications. The simulation results demonstrate the feasibility and effectiveness of the novel control approach. In the context of our review, this control methodology is active in Phase 3, triggered by the event changes observable through context based feedback information.

General form of regulators including nonlinear laws for Phase 2 of the proposed CACS formalism are commonly used for adaptation laws. This includes various forms of nonlinear control, optimal control such as H_∞ and generic compensator forms. Of particular interest is the latter, as it emerges from a generic formalism of existing system and control theory, and it is known as **fractional order control**. Advances in the past decade in this area provide enabling tools to design, tune, optimize, validate and deploy them onto real life processes. A vast amount of literature and software are readily available [39]. The most commonly employed tuning mechanism is based on performance specifications in frequency domain. These controllers are suitable for both Phase 2 and Phase 3 of the CACS formalism.

Supervisory control loops usually contain a mature advanced control methodology, such as **predictive control**. Model based predictive control encompasses properties of feedback and feedforward with ability to cope with constraints, delays and model mis-match, all present in CPSs [40], [41]. In this sense, the existence of a digital twin greatly increases the performance of the CPS, but it requires a great effort in the developing part of the CACS process [17]. Moreover, in the Industry 4.0 framework, product individualisation and on-demand product specification CPSs require versatile and flexible, albeit modular digital twin solutions [13]. Alternatively, if simple models are used instead, the effort shifts towards the design of the controller and optimization cost functions. For CACS purposes, this advanced control strategy may not be as relevant for the adaptation formalism, but for Phase 3 of the above mentioned concept.

V. SOCIETAL CHALLENGES

A. DIGITAL SOCIETY

In a hyper-connected world, evolving at an accelerated pace, IoT is at the heart of societal and economic challenges, while providing vast opportunities. This technology is interwoven in all domains of applications. Next generation networks managing large amounts of data require more bandwidth and wireless networks [42]. Smart devices use sensors (and thus data) to autonomously gather, share, analyse and interpret the information to make decisions. One of the most important IoT device is the popular smartphone, for which the techniques required in rule-based automated applications are presented in [43]. As digitalisation becomes the new standard, more data become available, requiring adequate tools to understand it and make it useful [44]. A driving innovation technology is cloud computing, enabling hardware, software and data available through internet [45]. As a result, increasing number of mobile applications appear on a daily basis, providing highly personalised information to users. Finally, a transversal aspect of digitalisation is electronic security for various aspects of data transmission [46].

An integrated approach to context-aware of web service systems is discussed in [47]. This work explains relevant CAS concepts, such as context information modeling, context sensing, distribution, security and adaptation techniques. Applications of CAS in mobile computing and IoT are presented in [24], [31]. They analyze a broad range of methodologies, models, applications and middleware connections related to context awareness and IoT. Another application in context-aware mobile learning systems is considered in [23]. It focuses on aspects that enable adaptive and personalized mobile learning for digital society services. A dedicated IoT survey with literature from both historical and conceptual perspectives while cross-linking the context awareness, machine learning, and big data is [48].

The concept of Big Data has required specialized tools for analysing and classifying this data, where context-aware recommender systems have appeared. Using this set of techniques, the decision-making process of the users is simplified by the suggestions made available through the leveraged contextual information. The progress of such CAS systems is overviewed in the work of [49], but without limiting to any specific application domain. There are highlighted the recommendation algorithms, the dimensionality analysis, the mode of representing the contextual information, but also the additions required by a CAS for recommendations in contrast with conventional ones.

The information sharing raises several challenges in complex organizational environments, such as a supply chain, where the economic activities vary, interdependencies between collaborators are very high and also the information usually takes different types. A method for deciding what parts of such complex context are considered relevant for clearly designing the CAS is analysed and applied in [50] for two study applications: tour guide and business-to-government information sharing systems in the container shipping domain. The complexity of such large-scale multi-stakeholder environments and international information sharing requires a context-aware system to support information sharing. The work proposes a method for efficient and effective design process by identifying what elements of the environment are relevant context. The ambiguity is avoided based on insight gain into context, which leads to the determination of the needed components from the context and the rules for how the system should adapt in different situations.

Still, despite the broad applicability of CACS, they have been introduced somewhat later into the industrial systems, because they rise problems such as diversity of data sources or privacy issues [51]–[53]. Additional examples are given in the domain of smart resource managament.

B. FOOD

The societal challenges regarding food industry are referring to quality, sustainability, health and supply chain optimization to reduce food waste. This sector is highly interdisciplinary as it crosses links with factory of the future concept in dealing with supply chain, raw food material use, product quality for nutrition and consumer safety, and overall production sustainability. In this thematic area, CACS based development is not explicit, but implicit, as the globalization of the food industry and food market naturally demands a context aware approach.

The integration of food supply chains with IoT technology has been addressed in [54]. It enables to monitor, control, plan and optimize remotely in real-time with validation on a fish supply chain management. A model based approach has been successfully presented and validated in [55] for monitoring aspects of product evolution, quality and safety during food processing. This is important to avoid bullwhip effects, which result in food waste along the supply chain [56].

Sustainability has been addressed in [57], [58], while emphasizing the vast opportunities for development in this area, as the current solutions are limited. A notable introduction of control theory in sustainable agro-food supply chain decision making, has been proposed in [59]. It proposes a multi-objective mathematical model to optimize the design of the supply chain network. This approach allows the simultaneous consideration of all three dimensions of sustainability including carbon footprint, water footprint, number of jobs created and the total cost of the supply chain design. It uses hierarchical process management, which is well suited with control methodologies such as distributed model based predictive control [60].

C. HEALTH AND WELL-BEING

CACS are highly relevant and already involved in many healthcare applications [61]. Even if context awareness brings significant benefits in health and care development, the solutions encounter many challenges in terms of interoperability between heterogeneous data sources, in context modeling and reasoning algorithms.

Context-aware patient monitoring can allow remote chronic disease management, elderly monitoring, wellness, applied in home care (as Active and Assisted Living (AAL) system) through IoT or in a non-fixed environment using wearable IoT. So called mobile health scenario provides friendly electronic health applications (smartphone-based or Internet-based), but also can be used as communication systems between the patient and their doctor, based on real-time alerts. Also, specific physiological or surrounding information may predict declines in the health status and transfer them as alerts to the patient or to the doctor. The critical role of CACS in managing cardiovascular disease is notably emphasized in [62].

The integration of CACSs and affective computing paradigms is proposed by [63] for building a mobile platform that identifies and interprets the affective state. Furthermore, a method for personalized detection of emotions is formulated and implemented through the use of wearable device. The architecture includes the adaptable model layer and the context-based controller layer for both physiological context acquisition and emotion recognition.

Clinical health care management is also a sector that can be improved through context-aware electronic patient record (as component of electronic medical record) [64]. For example, pathology patterns can be identified and patients in risk can be informed before they show symptoms, or the patient's context can be analyzed and a correct interaction process may be provided for assisting hospital staff activities. The most intriguing CASs in healthcare are the autonomic systems that receive feedback from patient's attached monitors or doctor actions (e.g., closed-loop anesthesia, robotic surgery).

Recently, assessment on health conditions based on the monitoring parameters is applied on chronic obstructive pulmonary disease (COPD) patients [65]. The CAS controls the vital parameters of the patient in relation to his demographic and medical profile, physical activity and environment. Based on an ontology reasoning, the monitoring infrastructure provides rules-driven recommendations, but also actions in real time. The results obtained 89% accuracy for physiological and environmental data identification, respectively 87% for nutrition information and physical activities. Moreover, tools from artificial intelligence provide better classification outcomes reviewed in [66].

Providing support to people in need of assistance, is a novel context-aware hazard attention system to be used on smart glasses [67]. For the assistive technology for impaired peripheral vision, the type and location of objects are detected with a deep learning object classifier. Their motion features are further extracted by tracking the frames appearance, speed and direction. Then, each recognized object is classified in levels of danger using a neural network classifier. Tests on public and private data sets shown a classification performance of 90% true positive rate, while the false positive and false negative rates were 7%, respectively 13%.

Another health-care system dedicated to people with movement disabilities is developed by [68]. The proposed assisted-living technology utilizes sensors and cameras in order to monitor individuals' behavior, based on which a virtual agent interacts with them. Heterogeneous data about user's body and his surrounding environment is collected, processed and saved using ontology language into models for profiles, activities, medical and verbal communication information, and relationships between them. The application brings benefits in hospitals to the caregivers, able to provide personalized advanced guidance to their patients or to detect patient falls. However, the patients can be assisted in their homes by this aware technology, through proactive action alerts in cases of emergencies or through vocal commands for adaptation of linked equipment (e.g., change of bed angle).

CASs have emerged in operation rooms under several applications that differ on their scope. Management of surgeries schedules can be improved through real-time supervision of operations, so a new application of CAS obtains online prediction of the duration of laparoscopic interventions [69]. Information from endoscopic images and surgical devices is classified with CNNs in different methods for prediction. Their evaluation on recorded interventions concluded that a combined method produces a lower average error (37%) than a singular method based only on vision or device data.

On the other hand, pervasive computing faces challenges while working with medical sensor nodes, where faulty data or even loss information can lead to false inferences regarding the patient's real state. Therefore, [70] propose a trust management scheme that avoids false alerts of the caregiver. The context-aware technology allows data fault detection (using heuristic, learning, correlation and time series analysis), data reconstruction (implying k-NN, clustering and Bayesian methods) and event detection (approaching single local detection, decentralized, centralized and distributed schemes). The proposed approach works with taxonomies of trustworthiness divided into different levels of rightness of medical data. The experiments proved that the context-aware scheme for pervasive healthcare is effective in detecting medical emergencies, but system initialization is needed.

Another challenge for the use of wearable sensors in pervasive healthcare is their battery life-time related problems. Thus, [71] introduce an aware wearable prototype that integrates both power-efficiency and physiological state prediction for remote health monitoring. Sensors for body and environmental data (e.g., temperature, humidity, accelerometer, electro-dermal activity) provide temporal and spectral features. These features are dynamically selected depending on the user's physical activity from that moment. This way, only the relevant sensors are active and a group lasso regression is used on them for further heart rate prediction. The contextual aware methodology successfully reduced the power usage of wearable platforms, while accuracy in heart rate detection was preserved.

One important application of CASs is their involvement in closed-loop control systems, but using non-invasive monitoring methods. An application which matured significantly over the last two decades is the automatic insulin delivery system [72], [73]. The introduction of control system theory in resolving context aware changes of glucose-insulin levels in diabetic patients has enabled great progress for patient comfort, well being and quality of life [74]–[76]. For example, the CACS proposed by [77], showed good performance in maintenance of glucose levels based on human activity recognition. The algorithm uses a CNN for classifying six different human activities direct influencing the glucose dynamics (jogging, walking, moving upstairs, moving downstairs, sitting, and standing), using smartphone accelerometers. The recognized activity along with the food intake and the past glucose readings are used as inputs by the glucose NN prediction model. Subsequently, a controller regulates the insulin bolus in order to bring the blood glucose levels within the safe limits. As such, mathematical models remain at the core of context aware drug delivery CPS control, either parametric based [62], [76], [78] or information based [64], and with potential for application to animal welfare [79].

Alternatively, human activity recognition is enhanced in Internet of Healthcare Things applications [64], e.g. by using semi-supervised deep learning framework [80]. Multiple motion sensor data, weakly labeled, obtained by various wearable devices is classified based on DQN intelligent auto-labeling scheme and fusion mechanism, while fine-grained LSTM model is applied for temporal features. Evaluation results reported in [80] based on the area under curve (AUC) indicated that the IoT framework obtained an AUC equally with 0.95, while other methods shown lower results (DNN, SVM, RF reach values of 0.87, 0.74 and 0.9 respectively).

D. SMART RESOURCE MANAGEMENT

The objectives encompassed by this societal challenge are to empower efficient use of resources, reduce energy consumption, have minimal environmental impact, enable growth and employment, while maintaining a competitive industry.

Naturally, industrial systems with context-aware features offer a high potential in energy efficiency, because it is influenced by several aspects. For example, industrial systems depend on the product type being fabricated, on the condition of industrial machines, on the ambient factors and on human experience [81]. Hence, building energy models of industrial machines have been developed based on the effect of context information [82]. These context variables are divided into regions based on Regression Trees algorithms, as they are suitable for continuous measured data due to fast computation. Further, by implying multiple Recursive Least Squares (RLS), a local energy consumption model is estimated for each region affected differently by the context. The validation of the multi-model approach is performed on a real cement plant in three different operating contexts (determined by the type of produced cement). The results show very accurate model's prediction, concluding that a model-based decision support system brings several advantages, such as better production strategies, less energy costs etc.

An application to design a context-aware assistance system, with the role of human-machine interface (HMI), for industrial applications is available using localization data [83]. These raw data such as user's location and role (e.g., operator, maintenance) are ontology-based modeled. Two application scenarios are extracted, as follows: indoor navigation pathfinder and dissemination of specific information related to a machine, both for the maintenance personnel. The first user interface is a virtual map that guides the technicians towards a nonfunctional machine, based on the acquired information (status of equipment, his own location, distance). The second scenario allows evaluating the functionality of a desired machine, whereas the application provides to the user the information relevant to his location and role. The proposed methodology that integrates context awareness into a proactive decision support system can be applied to any production infrastructure, using just camera monitoring. Hence, CPSs as part of industrial processes represent a big step-forward to self-optimization of manufacturing processes.

Aiming efficiency and productivity increase in manufacturing industry, several works imply context awareness, especially in flexible manufacturing systems, such as pharma industry [84]. An experimental application on shoe industry is given in [85] using ontology-based reasoning. It is applied to the injection machine, whose valves are automatically adapted by context information (e.g., air pressure and material type). It was observed that after training, the valves continuously change to an optimal frequency for opening, according to the injected material type. Optimizing CACS is also proposed by [86] in a real-time control and supervision of an industrial process of precision agriculture. It is proposed a multi-layered CAS that combines concepts as IoT, CA and Cloud computing. Environment and process sensors provide context data (e.g., soil humidity, temperature, pH and conductivity; light intensity, atmospheric pressure) that are stored in an IoT platform, all integrated in a framework of Cloud computer. The architecture has been successfully validated on an irrigation system. The controller proved to respond to environmental changes in order to maintain the set point, using classical rule-based inference techniques of Artificial Intelligence as context reasoning.

Utility processes in industry with demand side response framework into the energy grid are good examples where dynamic modelling is relevant for CACS optimization. The safety aspects of such processes are discussed in [87] from a thermal objective perspective.

Overall, closing CACS loops in a circular economy and implementing the factory of the future framework [81] are transversal to other challenges such as digitalisation and food [54], [55].

E. URBAN PLANNING, MOBILITY DYNAMICS AND LOGISTICS

These aspects of our society are highly interwoven, but a holistic approach to context aware system and control is not yet enabled. This is due to the high connectivity, data streaming and large flow of information within the IoT for such complex CPSs. Instead, we summarized below the most relevant challenges and solutions proposed in each of their thematic area.

1) URBAN PLANNING

The concept of context awareness is integrated in smart homes system usually by IoT sensor network. IoT encompasses interrelated devices and sensors that can transfer data over the entire network, and interact with the environment and the user [31]. For example, the contextually awareness of the user location and room temperature allows automatically switching on the light or air conditioner [88].

The analysis of the main works developed in this area is described based on the application's objective. A case study aiming energy use efficiency is tested on a university classroom by [89]. The context classification is designed with rule-based reasoning. A total of ten rules were associated with information of temperature, light, human presence, and power consumption sensors, reporting a high potential to improve energy use efficiency.

The ability of context-aware adaptation has been reported to improve the comfort and autonomy in a home. [90] propose a fuzzy classifier of ambient data for user's behavior recognition, in order to control lighting, appliances and temperature. Six behavior patterns are generated, using temperature, light and human presence. The study case concluded that the control response time was decreased with 6.98 ms compared to other architectures, while the precision was kept at 95.14%. On the other hand, two works to enhance comfort and home automation based on voice control are presented in [91], [92]. They use different classification algorithms of context data. In [91], the context is inferred using rule-based and Markov Logic Network reasoning, at the time of a vocal order or a risky situation for the user. The decisive context information is defined as activity, time and location after the processing of acquired data (speech, water consumption, lamp status, temperature and human presence sensor). In contrast, the application from [92] employs Deep Q Network (DQN) for context inference, any time the environment context changes. Thus, a graphical representation projects data on a two-dimensional map of the smart-home, integrating the context data from many heterogeneous sensors (e.g., temperature, contact-door and speech) into a unique image.

Both comfort and energy efficiency in buildings are analyzed by [93], using CASs for control of heating, ventilation, and air conditioning. The continuous adaptive environment model is learned using online NN with inputs of indoor/outdoor temperatures and power supply inputs. The work concludes that on-line control of terminal temperature is more stable and closer to the expected temperature. A combination of artificial intelligence tools with matured advanced control strategies is successfully employed in [94] to optimize overall energy consumption.

Activity recognition in order to lock the door automatically is published by [95]. The system consists of a Passive Infrared (PIR) Sensor Network that provides users movement data. However, it is considered low level data because of the lack of direct relation to the desired context, represented by the activity. To overcome this challenge, a non-conventional learning method is implied, namely Hierarchical Hidden Markov Model (HHMM). This approach brings high level attributes through activity recognition, by transforming the raw training data into activity information. It is hierarchical based, meaning that the number of learning levels determines a certain context. Comparing HHMM method with classical Naïve Bayes and HMM, the best performance to inference the correct security level was obtained by HHMM-based Context-Aware Smart Door Lock, with 88% accuracy.

2) MOBILITY DYNAMICS AND LOGISTICS

CACS is a natural approach for motion planning, cooperative objective optimization of unmanned vehicle platoons and fleet [96]. A notable survey is given in [97] for various vehicular applications discussed in terms of safety, traffic management, convenience, entertainment, among others. However, in situations where the human involvement is required (e.g., for disaster relief), are proposed the human-advanced-vehicle systems that are contextually aware. The relevant literature is analysed in the survey of [98], identifying further open research questions and opportunities.

Context-aware vehicular systems have gained intensive attention from both automotive industry and academia, because this concept is essential for advanced driver assistance, safety, fuel consumption efficiency and transportation networks. The context information applied on vehicles topic relates to any information that describes the driving situation. The vehicular applications of CAS are classified by environment, system-and-application, and context awareness [97]. Based on the driving context information, CASs adapt to the changing driving events.

Context awareness is integrated in Advanced Driver Assistant Systems (ADAS), providing improvement of knowledge about the states of the car, the external conditions and of driver's psychological state (e.g., attention, fatigue levels). Based on context-aware drive behavior detection, applications for ADAS, safety and fuel efficiency are further discussed in this subsection.

The literature revision reveals classification of drive behaviors that typically depends on the objective of the application. The driving style has an essential impact on fuel consumption and safety, as well as the technological characteristics of the car and the road conditions. Therefore, the awareness of driver states, along with the recognition of driving style and intention inference plays the most important role in CASs. These data about driving pattern (e.g., acceleration, speed), traffic conditions (e.g., location of the personal car and of the other participant cars in the traffic) and environmental information (e.g., slippery road, bumps) can be acquired through the available sensors integrated in the cars or part of other technologies (e.g., Global Positioning System (GPS)).

The terms mostly used in the main works developed in this topic are described bellow, in order to avoid misunderstandings and confusion, as no unique definition has been previously agreed:

- **Driving events** are defined as the maneuvers occurring during driving (e.g., acceleration, direction change). They are used to recognize the driver's driving style;
- **Driving pattern** describes the profile of position, speed or acceleration, including also the driving events (e.g., number of accelerations, time at constant speed, number of lane changes) extracted from the context analysis;
- **Driving behavior** relates to the driving patterns exclusively focusing on driver's decisions and neglecting external information;
- **Driving style** refers to the particular driver's way to operate the car, but in the combined context of human and external influences.

For the aim of transportation quality that concerns comfort, safety, and economy, a study on driving behavior, independent of external conditions, is presented by [99]. The context is estimated based on a classification framework of four behavior categories: ordinary, aggressive, unusual and calm. Using data acquired from the car diagnostic port, an additional accelerometer sensor and a GPS module, eight indicators (index-based) are obtained. They provide information about the vehicle's speed, acceleration, jerk, engine rotational speed and driving time. This method has been validated on several drivers. [100], [101] and [102] opted for more precise categories defined as normal, drowsy and aggressive behavior. These works have been developed for the objectives included in ADAS and driver safety applications. The classification method for driving behavior in [100] and [101] is based on fuzzy logic using driving events (e.g., acceleration, braking, turning, lane weaving, lane drifting, over-speeding and car following). Furthermore, driving style recognition is obtained through random forest method using characteristics of both driver and road [102]. Another ADAS application is proposed and simulated in [103]. The work divides abnormal driving behaviors into three categories: the fatigue/drunk, the reckless and the phone use while driving. The index-based classification method considers the driving events such as throttle position, speed and brake pressure.

Safety is another objective in CAS context-aware drive behavior applications. [104] and [105] define driving behavior as normal and aggressive, but their works differ through the used classification algorithms. In [104] are evaluated the following algorithms: SVM, Radial Basis Function Network (RBF), Logistic Regression, Bayesian Network, Decision Tree, k-NN and Naïve Bayes. By comparison, the SVM algorithm achieved an accuracy of 93.25%. Whereas, in [105] are analyzed Random Forest (RF), Random Feature Selection (RFS), and Long Short Term Memory Fully Convolutional Network (LTSM-FCN). The LTSM-FCN method reached 95.88% performance to differentiate between aggressive or normal driving behavior, characterized by six driving events such as speed, acceleration, orientation, car position relative to lane center, time of impact to ahead vehicle and road width. Finally, two recent articles that focus on safety have been presented by [106] and [107]. [106] propose three categories to classify driving behavior in calm, normal and aggressive, by testing five classification methods (SVM, ANN, fuzzy logic, k-NN and RF) based on acceleration, braking, deceleration and traffic violations. The experimental results showed the greatest accuracy (96%) for SVM. Deep neural nets seemed to be the best choice for road safety in term of overall performance, as shown in [108]. On the other hand, [107] includes acceleration, gravity, throttle, speed and revolutions per minute to recognize five types of driving behavior. They are listed in five classifications from normal to abnormal (normal, aggressive, distracted, drowsy, and drunk driving). Preliminary step converts the data into images, by applying overlapped time windows and recurrence plot technique. Then, a CNN technique classifies the aforementioned behaviors, allowing alerts transmission to driver or other vehicles via wireless communication technology.

The analyzed safety and ADAS oriented models are linked also to the objective of fuel consumption efficiency in vehicles, as many context properties are found to have significant effect on emissions. One work that considers changes in driving behavior for the design of a novel modified stochastic model predictive control is presented by [109]. It focuses on predicting driving events or repetitive cycles of a plug-in hybrid electric bus in an energy management strategy. While speed, acceleration and pedals position signals are the context observations for the K-means clustering of driving behaviors, the Markov chain-based driver models are developed for each category. In total, eight categories of driving behavior are generated and describe different levels for traffic conditions, slopes and speed. The proposed method was tested with the real-world bus routes, allowing 26.61% reduction of fuel consumption with respect to charge-depleting and charge sustaining control strategy, respectively 5.58% reduction compared to classical stochastic model predictive control that does not consider driver behavior model. A variant of the previous work with only traffic conditions level (six levels) is included in [110]. The events of speed, acceleration and pedals position are also employed to detect the most likely driving behavior, with a Fuzzy Subtractive Crusting (FSC) approach. An adaptive fuzzy controller mode, designed by particle swarm optimization (PSO) algorithm, regulates the power flow of fuel. With a prediction accuracy of 84% for driving recognition, a fuel consumption reduction between (9 - 17)% was obtained. Subsequently, the context-aware driver behavior system is implemented in a control strategy for an electric vehicle with dual-motor coupled drive-train [111]. This work aims to achieve reasonable mode switching and optimal power allocation between the two motors of the vehicle, under a known driving behavior. The driving behavior is classified according to driving events of speed, idle time, acceleration and deceleration, by means of Generalized Regression Neural Network (GRNN). The 96.08% classification performance provided 11.04% energy reduction under the urban driving behavior. Additionally, two more applications of fuel consumption efficiency for a plug-in and a series-parallel hybrid electric buses are proposed in [112] and [113], respectively. For both cases, the driving behavior identification is modeled using Learning Vector Quantization (LVQ) NN on speed, idle time, acceleration and deceleration. The adaptive rule-based control strategy from [112] outperforms the classical original rule-based control strategies (that exclude driving behavior) by energy consumption reduction of 4.94%. The results are motivated by the exploitation of driving behavior information beside the effect of operation in different conditions. A greater economy is reported in [113] (7%), considered to be caused also by driving behavior recognition. The proposed methodology consists of two levels energy management: i) a supervisory control to output the best operating mode and ii) a fuzzy control strategy to decide the components' power distribution that satisfies the total driving requirement.

3) ROBOTIC SYSTEMS

Context-aware solution is the essential part of robotic systems that provides the required context data through sensors. It allows robot systems to action automatically according to the environment, after being programmed by a computer. Usually, robots can be classified by the environment they are in and by the application field for which they are designed [114] (see Fig.6), so the following reviewed works use different types of robots. Important features of autonomous robotic systems are autonomy [115] and cooperative motion planning [116].

A context classifier of environment type (indoor, outdoor) in service robots is proposed in [117]. However, the architecture is scalable and permits the definition of many other context types. The classification technique used is Bayes Networks because the stochastic context data are also partially observable and have a sequential activity. Therefore, are used inputs such as temperature, humidity and light, number of satellites (from GPS), soil type (from inertial measurement unit (IMU)), gas level and time (day/night). The obtained classification accuracy was 87.5%.

Controlled robotic assistants have intensively emerged in surgery room environment, so [118] present a robot capable of adaptation of control strategy based on surgeon's activities. The clinical relevance of such a context application is improvement of safety and inference of the human-robot cooperation. This cooperation is critical for the knowledge about the time and locus that the robot should provide the most appropriate level of assistance to the surgeon. The classification of the current surgeon's activities is based on primitive human actions, namely *gestemes*. The online algorithm addresses gesteme-free activity classification because the vocabulary of gestemes is not required to be defined. The surgeon's activities models are described by Gaussian

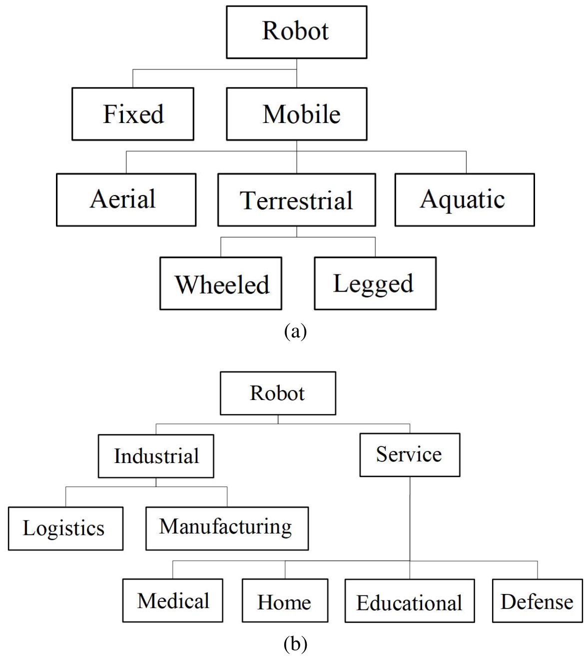

FIGURE 6. Classification of robots by (a) environment and mechanism of interaction, respectively by (b) application field.

distributions (low-level models), while Hidden Markov Models (HMM) (high-level models) ensure the switching between low-level models. After training the models using off-line processed data of 30 trials for each activity, the performed activities are classified based on forward-backward recursion implemented in the Robot Operating System (ROS). Thus, four main activities performed by the surgeon for different levels of assistance during hands-on robotic surgery are recognized in real-time: idle, wandering, leaving and approaching. Having intention-awareness, the robotic system smoothly adapts its behavior to the user's intention, addressed by Finite State Machine (FSM). The experimental trials evaluated the recognition of current actions at 80% accuracy after 450 ms. A related work with human-robot cooperation that supports people suffering of movement disabilities is developed in [119] by enabling them to regain motion functionality. By detecting the object of interest for the user, the context of the environment and intention of the user are extracted through CNN techniques. The system guarantees successful implementation for three types of movements: reaching actions (100%), pick and place task (96%), and pick, pour and place task (76%).

Autonomous Unmanned Aerial Vehicles (UAVs) are systems that require to be context-aware because they are defined to operate in uncertain environmental conditions. During unexpected obstacles, weather changes and sensor or other hardware/software component failures, UAV robots need to adapt. Adaptive control strategies based on robot model and hostile environments need to detect the failure in order to action. A work about context-aware diagnosis for UAVs is proposed in [120]. The status of the system components and appearance contexts are sensed. Next, the failure patterns are recognized by means of Bayesian logic, resulting in two failure scenarios related to the GPS and the battery. Additionally, a novel human-aware navigation for a mobile robot based on semantic maps and intention-awareness is introduced by [121]. The map is developed based on simultaneous localization and mapping (SLAM), where features for the semantic SLAM are planar surfaces (e.g., walls, tables) and static objects (e.g., door signs). Afterwards, optimal movement model is Bayesian-based estimated in order to update latent goals related inferences. Thus, intention-awareness is achieved by counterfactual reasoning. A quadrotor UAV used for surveillance and overhead monitoring is presented in [122] based on context aware iterative learning control strategies.

A two axis positioning mechanism is analyzed in [123] based on a context aware hierarchical control system approach. Previous learned solutions to previous tasks are used as the standing foundation for the development of a tracking solution. Reference inputs and controlled variables are used in a model free iterative learning control algorithm as library pairs to generate the next control action. The study solidifies the importance of context awareness in the robotics fields, providing context-based solutions that might eliminate the need of complex dynamics modeling.

Generic transportation systems with context-aware features are reviewed in [124] with specific challenges in marine systems [125] and aerospace industry [5].

F. NEW ENERGY DEMAND AND DELIVERY

The identified technological gaps in this area relate to sustainable energy supply, reduction of energy demand, and increase capacity and efficiency of energy storage systems.

Balancing problems of energy supply and demand are addressed in smart energy grids including information and communication technologies [126], [127]. Naturally, these CPSs require a context aware approach for system modelling and managing, while endorsing environmental preservation [128]. The increased utilisation of distributed renewable energy sources in low voltage grids leads to power quality problems such as overvoltages and voltage unbalance. For example, in [129], an energy storage system is combined with the classical positive-sequence control strategy and the three-phase damping control strategy to provide insight into power quality. A transversal review between smart grid and smart city framework is given in [130].

Renewable energy integration remains challenging due to stochastic nature of supply and demand in smart grid systems [131]. Distributed control seem to cope well with variations in operating conditions of power systems [132], while multi-objective optimization may offer versatility in short- and long-term economic objectives [133]. Multi-agent artificial intelligence algorithms applied to wind farm throughput optimization seems to be better positioned when data and structural features are integrated [134].

G. SOCIETY

Knowledge on people and society in general is indispensable in the socio-economic context perspective. Models from social sciences and humanities exist but not matured for utilization in a context aware driven society framework [135]. When society is addressed at large, interdisciplinary knowledge and cross-fertilization of tools are the the heart of a successful management policy [136]. A recent example is that of pandemic challenge, where global collaborations are crucial to provide social distancing mobile apps [137]. Also, it is important to keep in mind the social distancing policies to mitigate the COVID-19 spread in the population. To handle this several social distancing policies have been formulated. In [138], a Model Predictive Control (MPC) policy to mitigate the COVID-19 contagion in Brazil is proposed. This optimization algorithm allows to determine the time and duration of social distancing policies in the country. While other countries have opted for rigid social distancing measures, which has produced devastating economic effects [139].

Epidemics of given infections at a world-wide scale are integrated into the context aware paradigm through Reinforcement Learning (RL) and Monte Carlo control strategies in [140]. These tools are employed to develop a general model for general epidemiology, but with customization possibilities for particular infectious diseases. Outbreak responses can be managed using context-depended solutions. However, the challenge consists in translating different machine content to human decision makers, for particular policies.

VI. DISCUSSION AND CONCLUSION

CASs present interest to many applied industries because they assure assistance to users or to processes themselves, by self-adaptation of systems components. This is possible through acquiring, processing and disseminating the context data in real-time. Thus, a manifold of applications involving context awareness and CPSs have been developed in high impact industry domains and healthcare, which were analyzed in this survey.

Early applications have used context reasoning techniques such as Rule-based, Fuzzy Logic, Probabilistic and Ontology-based, because these methods are characterized by low computational cost and ease of implementation. However, recent innovation-driven computer systems have transferred the attention towards intelligent classification that exploits machine learning. This happened because microcontrollers and microprocessors allow implementation of such high computational learning algorithms.

As stated in the definition of CASs, the main benefit for using context awareness concept in a system consists on self-adaptation of its operation. It follows that control algorithms, structures and parameter values must be adapted to the current state of the context operation. For instance, automotive industry innovations center around advanced driver assistant systems and adaptive controllers, in order to improve one of the main challenge nowadays, energy consumption, in (hybrid) electric vehicles. Optimization of energy efficiency in buildings is also desired, but significant accent is still put to improve the comfort, autonomy and safety of users in smart homes. As energy consumption is also an issue in industry, adaptive plants have proved to achieve a reduction in energy, but also a greater efficiency and productivity of the processes. Future challenges for the cyber-physical manufacturing are reviewed in [81]. On the other hand, context-aware robotic applications aim to enhance human – robot cooperation and to benefit more from autonomous navigation considering human behavior. Finally, the integration of the context awareness instrument into healthcare CPSs brought advances in telemedicine and remote care solutions as IoT-aware AAL. Knowledge about vital signs of an individual, predicted based on actual contextual information, can avoid unsafe situations and personalized treatment.

The integration of control in the big picture framework of operation has several opportunities for research which are not yet addressed at this moment. We summarize here several such opportunities in various areas of applications.

For instance, in **manufacturing processes**, we have large scale processes with interacting sub-processes and mixed dynamics. There is the need for anticipating unexpected/gradual installation breakdown or disruptions, which may have tremendous financial consequences (e.g. ongoing pandemic). For instance, start up after breakdown may take days/months in processes as steel, paper, petrochemical or anaerobic digesters for watertreatment plants, etc. The cost of upgrading control loops is too high (70% of total expert deployment of control loops) [141]. However, large amount of data is available and can be used at its full potential.

Another commonly encountered application area is that where we have **mixed autonomous and human systems**. General example are assembly lines for **products and automotive industry**. The human in the loop has a high decision role in the operation and safety is the first concern, prioritized above high precision positioning and delivering elements to be assembled. Most of these loops are in open loop mode of operation in designated operation volumetric 3D areas and the human presence is a logic variable. This could highly benefit from a self-learning and self-optimization approach whereas the human in the loop with various degrees of expertise (new employer vs expert employer) can be integrated to aid and speed up the learning curve for the new employer.

A specific example of intelligent management system is the HEV (**hybrid electrical vehicle**). The operation of a HEV takes place in a fast changing environment and human behaviour has critical consequences upon the performance of the system as a whole. Changing settings as ECO, SPORT, SAFE modes require a self-optimization of the delivered torque as a function of context. Currently, the human related information integrated into the system is not exploited at its full potential. For instance, if multi-loop and multi-level information flow is used for self-detection of events (driver sleepy) can be used to optimize performance or endorse road safety. Or, another example: if event of driver sleepy (head tilted, eyelid closing) detected, then go to autonomous drive mode (if road context and road infrastructure allows) or identify first stop to self-park car or *drive to home* (predefined safety location). The mixed HEV optimization here included ensuring fuel/battery will suffice to reach either pitstop destination or home.

Another such application of a mixed information system is that of agricultural / heavy-duty machines for field operation. These contain many moving parts, belonging to independent but highly interconnected sub-processes, all linked to a single source of power/torque. The need is for self-diagnose and self-service on location, avoiding the cost of driving to service shop and minimizing the disruptive effect of a service stop. Diagnostics must take place in the field, whereas gradual/disruptive deterioration can be detected, and solution can be self-implemented *on location*. Operator decision based on alarm level can be used to self-optimize or return to base for repair. For example, if one of the internal mechanism is deteriorated, other sub-systems can operate at lower performance to allow the deteriorated one to have more power shifted to it; or multi-level loop restructuring may be used to discard using failed instrumentation (sensor or actuator) and use instead information from by-loops.

Finally, a highly relevant application is that of autonomous fleets and the connected car ecosystem concept. The objective is to have dynamic fleet management for autonomous mobility-on-demand. This can be done by self-optimization and self-decision of trajectory based on demand/utility/priority/traffic density/regulatory issues. For instance, an autonomous vehicle moving freely in a fluid changing properties. Climate change effects can be assessed by detecting changes in the density of the water/ice/silage/etc and measure contamination to determine affected area. Similarly, in nanomedicine, autonomous pill-size vehicle may travel along pulsatile flow in arteries and measure blood density, drug concentrations or detect/remove clogs along the way. Dependent on the context - in this case blood density - the information and decision-making procedures may vary. The battery use for propelling or actions (drug release, clog breaking, etc) may be optimized as a function of the environment and this is a fully self-triggered mode.

In general, the current operation of the CASs can be summarized in Fig. 7.

There are several technological barriers identified in the operation of CASs from Fig. 7.

1) *Industrial upgrade*. Operations are degenerative in terms of hardware wear and tear, software upgrades, human in the loop expertise is lost once replaced, etc.
2) *Robustness/Adaptability to (Un)foreseen Events*. Lack of methods and tools that can deal with (un)foreseen events in the operation/industrial environment, usually leading to performance deterioration and possibly shut-down (inoperability) of the machine/plant.
3) *Operability and Maintenance of System*. Lack of methods and supporting tools to maintain optimal operation of the machine/plant during specific/disruptive events.

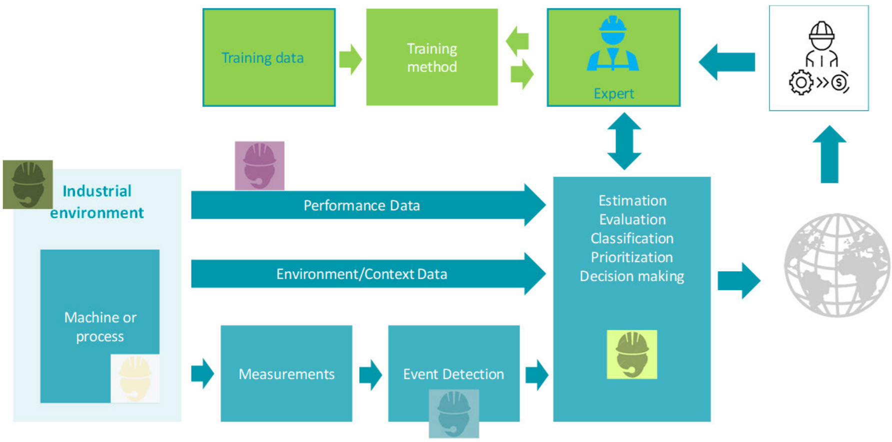

FIGURE 7. Illustrative concept of context aware control system where information flow is uni-directional and not approached globally; instead, decisions are made locally.

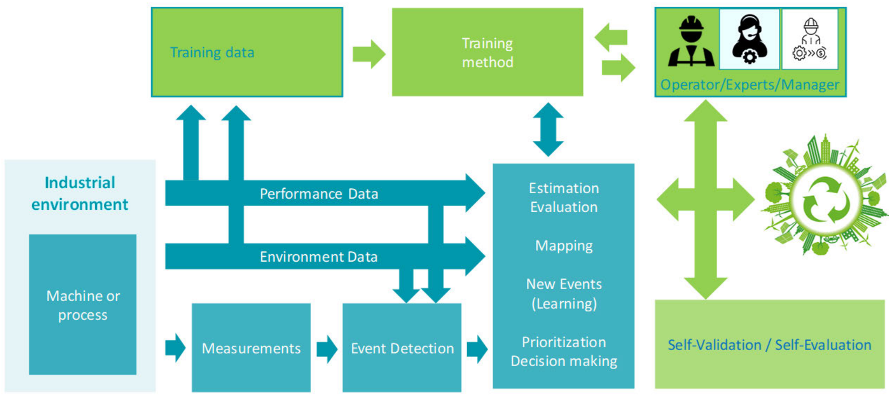

FIGURE 8. Proposed concept of context aware control system where information flow is multi-directional and approached globally.

4) *System (Self-)Sustainability*. Lack of methods and supporting software tools to ensure self-sustainability of the system under all circumstances and lack of learning from human expertise (decisions) during operation.

The proposed self-sustainable operation of the CACSs is given in Fig. 8.

To achieve the proposed operation of the CACSs as in Fig. 8, several challenges are necessary to be tackled.

1) to detect, map, learn and prioritize events in varying operating environments (resolved by CASs);
2) to trigger a self-evaluation and subsequent self-optimization mechanism
3) to provide continuous operation of plant/machine at all/most times, and
4) to move away from local to global self-sustainability of the plant/machine (i.e. a holistic approach).

If these challenges are addressed, the following objectives are achievable:

1) structural and parametrical adaptations at cross-level of operation
2) ensure continuous operation of plant/machine at all/most times
3) minimize or soften the curve of the economic cost of upgrading hardware/software and training human expert man-hours
4) capture, store and use operator experience: by asking operator feedback and incorporating that knowledge in the decision mechanism (but enables bidirectional flow: operator also learning from self-optimizing decisions).

A focal point in the study and assessment of context aware solutions are the cyber-security risks targeting a large scale system [142]. Large scale knowledge sharing creates cyber-vulnerabilities such as data loss or data theft, branded exploits against machinery, hacktivism, phishing, etc [143]. From the society perspective, the greatest threat consists in the individual itself [144]. Combining the individuality of a Society subject with the intrinsic data retrieval property of the Digital Society, various contextual information characterizing the individual is shared with external sources. Hence, a person may receive personalized suggestions dependent on its present life context, opening the door to a manifold of security threats such as social engineering attacks and targeted executive threats [145].

To conclude, context aware systems require a supervisory mechanism for self-monitoring, self-evaluation, self-classification of the condition of machinery and final products with the final purpose to self-optimize the global performance of a process/machine that works robustly in an industrial (varying) environment.

APPENDIX

LIFE-CYCLE OF CAS

Acquisition process involves several challenges are brought up by multiple and distributed sources (e.g., lower quality of the information), possible inaccurate or missing data from sensors, addition or removal of sources (e.g., scalability issues) and sharing of sensors and service resources between many users (e.g., difficult to acquire the information) [21]. It follows a set of determinant factors used to acquire context and to vary the context-aware solutions:

- Responsibility. The communication of the responsible software component with the sensors can be pull-based, when the software requests data from the sensors, or push-based, when the sensor pushes the data to the software;
- Frequency. The acquisition can be instant, known as event-driven action, or interval-based, when sensors collect data about events over certain period;
- Source. Sources of data can be the sensor hardware, a middleware infrastructure or context servers (e.g. public databases or web services);
- Sensors types. There are three possibilities: physical (e.g., digital or analogue outputs), virtual (retrieve data from many sources and present it as sensor data) or logical, that obtain more relevant information from the merge of physical and virtual sensors;
- Acquisition process. The context data can be acquired in three ways: sensed through sensors, derived by computational operations of raw sensor's data or manually provided by the users via preferences.

Modeling of the context can be considered the most relevant component of CAS. The acquired sensor's data have a form that can be used by computing components, but may be non-understandable to the user, requiring translation into meaningful terms. Such models involve the representation and unique identification of context information through its entities and their relations. They need to be simple, reusable, expandable and ready at run-time, but also able to validate pieces of data and encode its uncertainty [30], [146]. Context modeling is implemented through several approaches [147]:

- Key-Value. The models are name-context value pairs, usually independent to other pairs. These models are suitable for limited amount of data (e.g., user preferences, application configurations), being simple enough to describe it;
- Markup Scheme. Commonly modeling hierarchical data structures, these models use mark-up tags, attributes and content. The models are defined based on XML languages (Extensible Markup Language) for encoding context information in a format that is both human-readable and machine-readable. Markup schemes can enable the format for intermediate data or the mode of data transfer over network (among applications or among application components);
- Graphical. Graphical models capture relationships within the context and are mainly represented by databases. The modeling techniques use Unified Modeling Language (UML) and Object Role Modeling (ORM). They allow storage of large volume of data, but also quickly operations of data retrieval;
- Object-oriented. The models exploit class hierarchies and relationships through techniques such as encapsulation and inheritance. The context is thus presented in a high-level programming language that supports object oriented concepts. Consequently, object-based modeling provides context run-time manipulation and supports data transfer over network;
- Logic-based. The models take advantage of facts, expressions and rules, in order to derive the highest context knowledge compared to the other modeling techniques discussed previously. Therefore, they are suitable to be used for modeling policies, constraints and restrictions;
- Ontology-based. The models provide ontologies that describe taxonomies of concepts and even relationships. This approach shares a common understanding of context data among different software and users, assuming interoperability and re-usability of shared knowledge. Besides, ontologies provide the structure for data stored in relevant sources. The models are constructed using popular ontology languages, such as Web Ontology Language (OWL) and Resource Description Framework (RDF).

Reasoning or evaluation of the context is described by extraction of new knowledge from the modeled data of the available context [147]. This step can be divided into three phases: i) pre-processing of context data to eliminate inaccurate values; ii) fusion of sensor data to generate more precise information; iii) context inference to obtain new context information from lower-level context sources [31]. Techniques for processing the contextual available input can be classified as learning or inference, as follows:

- Supervised Learning. It is a classification technique that maps the input context sets to an expected output, in order to generate a function able to yield results from labeled training data. Examples: Decision Trees, Bayesian Networks (BN), Artificial Neural Networks (ANN), Support Vector Machines (SVM);
- Unsupervised Learning. It is a self-learning clustering technique that discovers features of the input context, based on unlabeled data. Examples: K-Nearest

Neighbors (k-NN), Kohonen Self Organizing Map, Noise and Outlier Detection;

- Deep learning. It is based on ANN that use multiple layers to progressively extract higher level features from the input context. The networks are capable of unsupervised learning from the interaction experience with the environment, resulting in improved performance of the task. Examples: Multilayer Perceptron (MLP) Neural Network (NN), Back-Propagation NN (BP), Convolutional NN (CNN), Recurrent NN (RNN), Long Short-Term Memory NN (LSTM);
- Rule-based. The algorithm is in the form of traditional "if-then-else" schemes. Another alternative is the association of IDs to entities (e.g., radio-frequency identification);
- Fuzzy Logic. It is known for reasoning about vague information, based on "degrees of truth" rather than the usual "true or false" Boolean logic. Fuzzy logic is intended to approximate the truth, where the confidence values represent degrees of membership rather than probability. It resembles human reasoning and natural language;
- Probabilistic. The method infers a decision based on the probabilities associated with the real facts, handling uncertainty. Examples: Dempster-Shafer, Hidden Markov Models (HMM) and Naïve Bayes;
- Ontology-based. The reasoning is handled based on ontology modeled data, using semantic Web languages, such as RDF, RDF schema (RDFS), and OWL. The possibility to combine them with ontology modeling makes this reasoning more advantageous.

Dissemination of the context-related information is the final step towards the consumers (e.g. users or applications) in the process of decision making in CPSs. The following features are required for this step: high available context information and real-time distribution. From the usage point of view, we further distinguish between two approaches:

- Query. The context-related information is disseminated when the context consumer issues a query for updates;
- Subscription. The information is revealed to the customer triggered by events, based on apriori settings with the context management system.

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