An Embedded Intelligence Future Vision of Flexible Configurable Manufacturing

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Abstract

While current Embedded Intelligence solutions provide many more sources of digital information, they need to be developed from a more inclusive business perspective if they are to fit with the holistic requirements of business which requires the ability to interoperably share information as well as to dynamically update system configurations to meet the rapidly changing needs of successful companies. This workshop paper considers the solution requirements to meet future manufacturing needs from an embedded intelligence perspective, anticipating the need to find solutions that are configurable to meet the multiple differing knowledge requirements across the range of manufacturing business types as well as being flexible enough not to constrain businesses against their necessary change requirements.

Keywords 1

Embedded intelligence, interoperability, manufacturing, knowledge, rapid change

1. Introduction

Information and Communications Technologies are pervasive in manufacturing but tend to offer many solutions to very specific problems. There has been a recognition for some years now through ideas like Industrie 4.0, the drive towards Smart Manufacturing and Digital Twins and the exploitation of Cyber-Physical systems, Internet of Things and Artificial Intelligence that the growth in digital information should help manufacturing businesses to be more competitive from a holistic perspective. While current Embedded Intelligence solutions certainly provide many more sources of digital information, they need to be developed from a more inclusive business perspective if they are to fit with the holistic requirements of business which requires the ability to interoperably share information as well as to dynamically update system configurations to meet the rapidly changing needs of successful companies.

This workshop paper considers the solution requirements to meet future manufacturing needs from an embedded intelligence perspective, anticipating the need to find solutions that are configurable to meet the multiple differing requirements across the range of manufacturing business types as well as being flexible enough not to constrain businesses against their necessary change requirements.

2. Issues related to Embedded Intelligence

At its heart embedded intelligence provides data about the artifact in which it is embedded. This data may be used in real time or may be accumulated for subsequent analysis for a broad range of purposes.

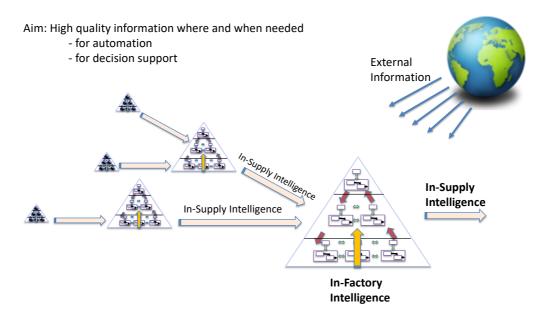
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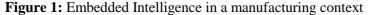
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From a manufacturing intelligence perspective this can be considered as providing in-factory intelligence from shop floor machines or as proving in-supply intelligence as artifacts are moved through suppliers and on to customers and consumers as illustrated simply in figure 1.





Questions that are worth consideration in relation to the provision of this data are (i) Is this data a true reflection of the status of the artifact? (ii) Can this data be analysed effectively to control or learn about the artifact? (iii) Can this data help decision makers to improve the quality of their decisions?

The extent to which any of these questions can be answered positively is dependent on the manufacturing business context in which embedded intelligence is being applied and any external factors that also need to be considered.

In simple control systems embedded intelligence has been successfully used for many years. However, problems can occur when:

- Multiple data sources are required in potentially harsh environments
- Where information is collected or used across multiple software tools.
- Where information is required across multiple business roles e.g. machine operators, shop floor managers, maintenance engineers, production planners.

The fundamental question remains: how can we get the right information to the right place at the right time and in a form that is readily understandable and actionable by the user? Added to this we have the further critical question: how can we provide solutions that are flexible enough to meet the dynamic change requirements of businesses that need to rapidly react to evolving markets and new business models?

It has been argued in the past [1] that the key technologies that need to be addressed related to embedded intelligence for manufacturing business support are analytics technologies, applications services, workforce toolkits and interoperable knowledge environments. However, while the provision of these are certainly important, they need to be offered within intelligence development environments that can meet the dynamic change requirements mentioned above.

3. An Embedded Intelligence Framework Vision

The key issue looking forward is how to provide key technologies for EI in a way that is easily configurable and re-configurable. To do this requires a deeper understanding of the knowledge that underlies the options available for each aspect of developing an intelligent system as well as a clear

understanding of the anticipated business requirements for the design and operational requirements of that system. An illustration of this is provided in figure 2 with an explanation of each area described in the sub-sections below:

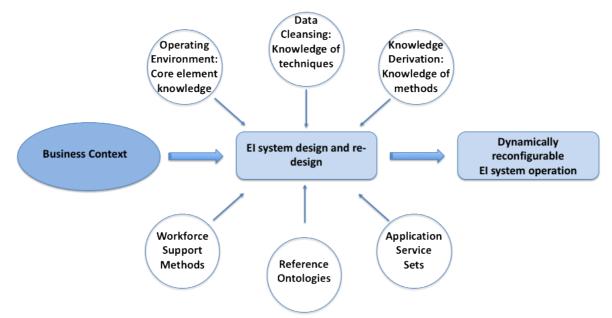


Figure 2: Key elements of knowledge support for future EI manufacturing systems

3.1. Business Context

EI can offer business opportunities in every part of the manufacturing system: from the design of the factory to last mile delivery in product supply. Observing the condition of a product (and the parts it is made of as well as the machines and humans interacting with the product) throughout the manufacturing process increases the chance to predict problems earlier [2] and therefore increases the efficiency and effectiveness of the manufacturing system.

For example, monitoring workers and parcels in the last mile delivery process increases the security through traceability and allows identification and fixing of problems experienced by workers to increase their performance through supportive equipment and human-centric optimization of processes. The knowledge gained from the observational data can feed into cyber physical systems, increasing the predictability of the manufacturing process by improving transparency, understanding, decision making and offering opportunities for self-optimisation [3].

3.2. Operating Environment - Core Element Knowledge

There are several elements of a system that can be affected by the operating environment including sensors and communication. Therefore, having the appropriate knowledge available of the environment and how it effects the embedded system is important for making the design robust. An example of this is the communication of an embedded system as it is important to consider the location of antennas and the materials of products they are attached to especially if there is metal. Having reliable wireless network performance of an EI architecture will also depend on the mobility of devices that all compete for the same shared wireless medium as well as the mobility, density, granularity and material makeup of obstacles in the immediate environment. [4]. Having knowledge of all the core elements that need to be considered and understanding of their interrelationships will support effective EI system design and rapid re-design when required.

3.3. Data Cleansing – knowledge of techniques

Raw data collected from embedded systems requires cleansing to guarantee it is consistent and suitable for further data analysis. Consistent data requires the data to be complete, contain no missing or invalid entries and be distributed correctly for the domain of analysis. The data cleansing processes includes error confinement, standardisation and 'bad data' removal.

Error confinement ensures that, if errors exist, those are treated in a way that is appropriate within the business context proposed; this may involve filtering erratic data, outlier identification and management with a study of error propagation in the dataset. It is crucial to develop a strategy to eradicate 'bad data' that can be due to incorrect data entry, data corruption or duplication of data points. Cleansing techniques require a comprehensive knowledge and understanding of the specification of the embedded system from which the data originates, the conditions in which the data has been recorded and the domain in which analysis is to be conducted to enable interoperability of data from embedded systems for further data analysis.

3.4. Knowledge Derivation – Knowledge of Methods

Knowledge derivation is a broad topic where a number of techniques are applied to data to enable insights to be drawn, new knowledge to be inferred with the aim of developing services and supporting decision making. Knowledge derivation entails several different processes including traditional data analysis, artificial intelligence, modelling, simulation and digital twins.

These processes can be implemented through a vast number of different techniques and algorithms (e.g. Monte Carlo simulation, convolutional neural networks, Hidden Markov models), each providing a specific functionality within the knowledge derivation process. A challenge for developing reusable and interoperable embedded systems is how to best select appropriate techniques to perform a given task, based upon the specific end user requirements whilst anticipating any potential negative implications of a particular technique. Additionally, how to gain confidence in the results of an analysis process, for example is it causation or correlation?

3.5. Workforce Support Toolkits

Considerations for effective support of workers include tasks, environment and users [5]. Due to the increasing variety and complexity of tasks anticipated within future manufacturing systems, a range of multimodal support tools are required to ensure effective interaction between humans, autonomous and system elements. The human workforce is required to interact with, interpret and effectively contribute to systems comprising a mixture of human and machine intelligence and autonomy. Interfaces will be required that make information visible to the human and offer human visibility to the system. In addition to worker support, any techniques employed to facilitate these interactions will need to comply with security and privacy regulations including GDPR (General Data Protection Regulation).

Research is required to standardise approaches in order to facilitate interoperability for virtual collaborations, distributed networks of collaborators and customer bases. Questions arising include how best to capture requirements, assess worker/task compatibility, capability and training requirements, legislation compliance, cost/benefit and minimisation of potential negative effects of work on the humans and the system including risk, fatigue, workload and error mitigation.

3.6. Application Service Sets

Application service sets provide generalised functionality aimed at supporting tasks within the manufacturing domain (i.e. object location detection, condition monitoring and process traceability). While analytics technologies provide techniques that can be generally applied to identify useful

information, application services package these techniques in a reusable and on-going manner to support particular business needs and develop cyber physical systems [3].

A key challenge for developing EI in future manufacturing environments is how to adapt and reuse existing applications services to meet the requirements of similar problems but within different domains rather than reinventing the wheel for each specific application.

3.7. Reference Ontologies

A key factor in the successful uptake and future proofing of an EI system is the validity of the knowledge used by and gathered from the system. Reference ontologies support interoperable data sharing, reuse and maintenance by providing an agreed and updateable authority on the domain. Querying the ontology can then enhance capabilities in sustainable and responsive decision-making and be used to answer questions regarding future system states, provide a probability of hitting a target or an estimate of whether there is a high risk of a threat occurring.

An EI reference ontology should draw together and formalise the understanding of terms and relationships across the domain and previously discussed in this paper. Both a collaborative approach to development that includes domain experts and an accordance with a widely used top-level ontology can ensure the inclusion of complete knowledge, logical consistency and accuracy in representing the domain. Continuous update of the knowledge ensures that the ontology continues to be used and supports time critical decision-making e.g. in reflecting current market changes. Appropriate update will depend on human, network and system input and the capability to draw from legacy and future knowledge bases, using ontology merging and technologies such as natural language processing, machine learning and web scraping. Trust in using the ontology will then depend on validation in use – how consistently does a query of the ontology produce the right answer.

4. Discussion and conclusions

This paper proposes a knowledge framework, focused on methods by which the underlying knowledge of the key aspects of embedded intelligence systems can both be modelled and exploited to support the flexible design and operation of such systems. The ability to build such knowledge models as well as capture the key interrelationships that exist between them, will provide an underpinning framework that can meet the dynamic reconfiguration system needs of manufacturing businesses.

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