Modelling Knowledge Dynamics in Industry 4.0 - A Smart Grid Scenario

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Abstract
New digital technological advancements are giving rise to the fourth industrial revolution, commonly termed as Industry 4.0, in which the physical and the digital world merge and the boundary between products and services blurs. This transformation is powered by smart, autonomous objects that communicate and interact among themselves or with actors through the connected, multi-loop, and multi-layer network of Internet of Things and Services. These interconnected smart objects create, carry, and share large volumes of data, leading to many potential opportunities for creating value from such data. Albeit particularly Big Data has been a much-discussed term in research concerning the Industry 4.0 paradigm, the role of knowledge, especially tacit knowledge has been neglected thus far. Furthermore, a conceptual model that would provide an aggregated framework to understand knowledge-based activities and flows does not exist yet. In this paper, we attempt to bridge this gap by firstly critically examining and clarifying the terms data, information, and tacit knowledge by drawing upon relevant knowledge management theories, foremost on Polanyi`s, a common (albeit often misinterpreted) reference point for his successors. Then, by reviewing and analyzing related literature, we develop a conceptual model of knowledge dynamics in the Smart Grid ecosystem, which is one of the potential application fields of Industry 4.0. Specifically, we conceptualize main components and their relations, and describe how knowledge-based activities are embedded in the multi-feedback loop and multi-layer network of Internet of Things and Services. We exemplarily outline a use case – a Smart Grid program of CLP Holdings Limited, the largest supplier of electricity in Hong Kong – as an example of how value is co-created through knowledge dynamics within such ecosystems. Furthermore, we discuss the theoretical and practical implications of the emerging knowledge dynamics model for the design of knowledge management systems.

Keywords: Knowledge Dynamics, Big Data, Tacit Knowledge, Industry 4.0, Internet of Things, Internet of Services, Smart Grid, Knowledge Management Systems

1. Introduction

A new industrial revolution is starting to take place, commonly termed as Industry 4.0. For the first time the revolution is predicted *a-priori*, not observed *a-posteriori*, which enables public and private sectors to actively create the future as it unfolds (Hermann et al., 2016). The wide interest in Industry 4.0 is evidenced by numerous research and strategic initiatives proposed by main industrial countries, which aim to develop more intelligent and sustainable industrial systems. The term itself became publicly known with a strategic initiative called "Industrie 4.0" which is a part of the German government`s "High-Tech Strategy 2020 Action Plan." Similarly, China announced its research initiative "Made in China 2025" and USA it`s initiative "Industrial Internet".

Industry 4.0 provides several application fields: smart production, smart grids, smart logistics, and smart healthcare (Leitao et al., 2016). Our knowledge dynamics exploration in Industry 4.0 is informed by industrial smart grids (SG). The foundation of SG is strong coupling of digital technologies with the physical energy domain, particularly via mass deployment of smart objects (SO), i.e. networked embedded devices (e.g. home appliances, electric vehicles). The symbiosis of digital and physical domain enables bidirectional energy and communication flows among participating entities and promises to equip physical resources with adaptive emergent capabilities that commonly characterize social and biological systems (Leitao et al., 2016). These characteristics lead to a distributed, reconfigurable, hyper collaborative and interconnected industrial environment which enables new interaction patterns and business models. Particularly, penetration of "service dominant logic" (Lusch et al., 2007) blurs the line between products and services, and leads towards product-service system business models, characterized by always-responsive situated services built around customer needs (Miorandi et al., 2012; Monostori, 2014).

The shift towards responsive and situated service provisioning is brought to the table by a huge amount of fine-grained data, collected, stored, and processed by SO. Thus, organizations seek to find processes to turn such big data into knowledge and meaningful insights. Whereas these processes can be automated to a great extent by using big data analytical tools, so far not sufficiently considered is the role of humans in-the-loop (Gandomi and Haider, 2015; Leitao et al., 2016). This is particularly relevant for Industry 4.0, which is characterized by democratizing access to data, i.e. opening data to various stakeholders via diverse web-based or mobile applications, which provides more possibilities for their engagement. It becomes important to leverage on these open data by making it available to the right stakeholders at the right time to support their decision making (Marr, 2017). Taking the "human factor" into consideration raises questions such as: *What is the role of human knowledge in unlocking the value of big data? How can humans interact with SO and make sense of by SO generated data?* Whereas existing contributions partially analyse these topics, a holistic perspective that integrates various theoretical strands regarding knowledge-related activities that lead to value creation in SG does not exist yet.

In this paper, therefore, we conceptualize a model of knowledge dynamics as an underlying mechanism of the emergent behaviour that promises to bring new, more sustainable value chains in SG industrial systems. But firstly, we begin by reconsidering knowledge theories and seeking answers to epistemologically fundamental questions such as *What is nature of knowledge?* (2.1) and *What is relationship between knowledge and technology?* (2.2). Furthermore, we discuss issues of modelling knowledge dynamics (2.3). Afterwards, by analysing current literature, we extract components of SG which are applied in the conceptual model (3.1) and describe its operational mechanism as an enabler of the value chains that it creates (3.2). Subsequently, based on the publicly available documentation and the interview with a manager in charge of SG program, as an example case, we highlight the efforts within CLP Holdings Limited pilot projects and currently offered services (3.3). The paper closes with a discussion of the implications of the proposed model (4) and a conclusion (5).

2. Knowledge dynamics

2.1 Dual nature of knowledge

There are two major streams in the philosophy of knowledge literature that can be identified – one rooted in positivism – which perceives knowledge as an artifact that can be deconstructed into discrete units, and another in constructivism – which perceives knowledge as socially constructed and embedded in practice (Hislop, 2002; Stenmark, 2002). One of the positivists' foundational assumption is the tacit-explicit knowledge dichotomy, i.e. that knowledge can be divided into two types with distinct features (e.g. Nonaka and Takeuchi, 1995). The constructivists' underlying assumption, on the contrary, is the duality of knowledge, i.e. that tacit and explicit knowledge are indivisible and mutually constituted (Polanyi, 1966; Stenmark, 2002; Tsoukas, 2005).

We base our understanding of knowledge on Polanyi`s (1966) theory, which is grounded in constructivist rationale. He is pondering knowledge in terms of the duality, i.e. knowing occurs in the dynamic interactions between always present subsidiary tacit knowledge components and a focal target (Polanyi, 1966). For example, a pianist has the ability to play the piano, i.e. tacit knowledge enables him to perform the action of playing a piano. However, the pianist is only subsidiary aware of such knowledge – *he knows more than he can tell* (Polanyi, 1966). The object of his focal awareness is the music itself. An attempt to focus on the technical ability, e.g. on how to move his fingers, would make his "performance clumsy to the point of paralyzing it" (Tsoukas, 2005). Since the integration of the subsidiaries to the focal target relies on the internal tacit act, tacit knowing is inherently inarticulable (Polanyi and Prosch, 1977). Polanyi furthermore claims that even what often is considered to be detached objective knowledge, such as a mathematical theory, "can be only constructed by relying on prior tacit knowing and can function as a theory only within an act of tacit knowing" (Polanyi 1966: 20). Thus, in the case of our piano player, his music will be differently "heard" by every individual depending on the personal knowledge which includes, among other, personal commitments, skills and judgments; equally, the interpretation of music notes will vary for the same reasons (see Fig. 1).

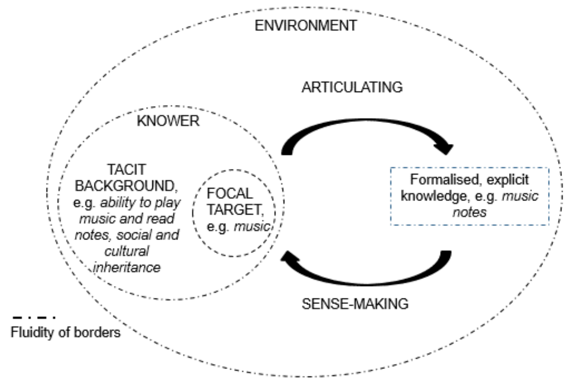

Figure 1 Dynamic relations that comprise knowing

The dual notion of knowledge, as introduced by Polanyi, implies the intrinsic emergent property of knowledge: knowledge is an "act of relating" (Kakihara and Sørensen, 2002). Polanyi`s notion of knowledge was often misinterpreted by his successors, most notably Nonaka and Takeuchi (1994). They posited that tacit knowledge can be converted – *to great degree* - to explicit knowledge, i.e. that it can be articulated in a form of concepts, models, hypotheses, metaphors, or analogies. However, such a view is not congruent with Polanyi`s, who considers tacit as indivisible and essentially unspecifiable part of all knowledge.

2.2 Knowledge and technology

In knowledge management literature, particularly when discussing relationship between knowledge and technology, it is often emphasized that it is valuable to differentiate data, information, and knowledge. One important point of discussion is whether human knowledge can be formally described so that a digital machine can handle it. Positivists would seek to utilize technology for handling a representationistic understanding of knowledge. Constructivists, on the contrary, would argue that human knowledge cannot be separated from the knower and that what can be found outside in a formalized, explicit form is merely data and information (Stenmark, 2002). While arguing that tacit components of knowing, since inherently unspecifiable, remain beyond calculative rationality that computers can simulate, we believe that it is useful to use the term machine knowledge. Whereas what constitutes these concepts inevitably alters with advances in technology, the essence remains: they are based on logic that can be specified and, thus, programmed and automated (Ackoff, 1989).
Further consequential argument adopted by constructivist is that there is no "raw data"; data emerge as result of a pre-defined data structure, which defines the meaning of the phenomena sensed from the environment (Tuomi, 1999). While acknowledging the possibility that, due to unique tacit background of the interpreter, "what one conceives as information another sees as data" (Stenmark, 2002), we consider t as useful to differ the two in terms of their functional differences (Ackoff, 1989). Thus, one way is to perceive information as data that is processed into a usable form (Table 1).

Table 1 Knowledge entities: definitions, properties, and activities

	DATA	INFORMATION	MACHINE KNOWLEDGE	HUMAN KNOWLEDGE
Definition	Symbols that represent properties of objects, events	Descriptions, processed data into usable form	Ability to apply programmed instructions, learn	Act of relating, dynamic capability
Properties	Based on logic that can be programmed and automated			Emergent, depended on personal knowledge
Knowledge-based activities	*Data processing and analytics*			*Sense-making, dialoguing with data*

Adoption of the constructivist view on knowledge has important implications on the perception of the relationship between humans and machine-generated data and information. Since the "act of personal insight" is inherent to the act of knowing (Tsoukas, 2005), human active involvement is still required. Whereas data

analytics are just one stage in unlocking value of data, humans still need to make sense of reports (new data and information), which is "a motivated, continuous effort to understand connections […] in order to anticipate their trajectories and act effectively" (Klein et al., 2006). This might involve critically testing assumptions, tracing backward the analysis, and discarding some aspects of the data (Labrinidis and Jagadish, 2012). Insights, then, emerge as a result of sense-maker`s engagement with the data, and will vary depending on the sense-makers' personal knowledge. This is "a process of dialogue rather than one of discovery"; insights can only be "evoked by the data" but cannot be "explained from the data" (Bryant and Raja, 2014).
In Industry 4.0 context machines are capable of (deep) learning, adjusting and acting in its environment, such as in the case when they exploit neural networks that aim to mimic the thought and decision-making process of humans. Still, humans handle resulting data indifferently. Machines, hence, can only be considered as a supporting part in collective sense-making processes.

2.3 Modeling knowledge dynamics

Existing models of knowledge dynamics have limitations in representing the dynamic, emergent property of knowledge. They are based on two metaphors: *knowledge as a flow*, which focuses on how knowledge moves through organizations and *knowledge as a process*, which focuses on explicit knowledge or knowledge conversions between tacit and explicit knowledge (Bratianu 2016). Both conceptualizations are largely rooted in the positivistic logic, and disregard the fact that paradoxically and simultaneously knowledge is both a thing and a flow. They do not acknowledge that tacit knowledge can only be displayed in human actions, and that thereby knowledge dynamics model – instead of attempting to operationalize it (Ambrosini and Bowman 2001) – should identify spaces of human-human and human-machine interaction which enable emergence of knowledge. In such an attempt, it might be useful to build on Nonaka and Konno`s *Ba* (1998) as a "shared space for emerging relationships." *Ba* can be mental (e.g. shared experiences), virtual (e.g. networks), or a physical place (e.g. factory). Moreover, *Ba* unifies these spaces "in order to profit from the 'magic synthesis' of rationality and intuition" that creates knowledge (Nonaka and Konno, 1998). *Ba* is a context which provides the basis for human interpretation of information to create meanings and knowledge through action and interaction; knowledge resides in *Ba*, and if separated from *Ba*, it becomes information (Nonaka and Konno, 1998).

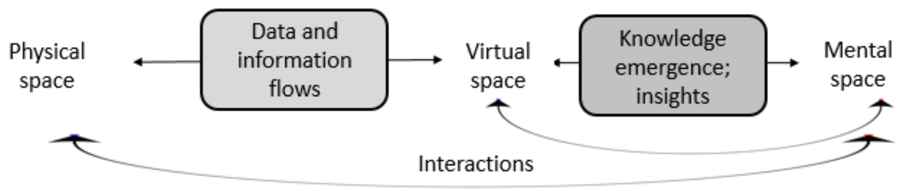

Figure 2 *Ba*: Topological space for knowledge emergence

Ba, since it exists in terms of relationship, and it permits to relate human interaction and emergent property of knowledge to knowledge practice, seems to be a useful concept to utilize as a building block in knowledge dynamics modelling.

3. Conceptual model of knowledge dynamics in smart grid scenario

3.1 Theoretical underpinnings

(Hermann et al., 2016) provide a useful basis for developing utilized constructs within the conceptual model. They identify components for implementation of Industry 4.0. However, since they perceive smart factories as "key ingredient of Industry 4.0", their analysis and descriptions of components focuses primarily on smart manufactories. We adopt their framework by reviewing current literature on SG and identifying industry specific components. Overall, we identify five main components: *Smart objects*, *Smart grid*, *Cloud-based Internet of Things and Services*, and *Humans in-the-loop.* As a critical difference to Hermann et al. (2016), we involve *Humans in-the-loop* as an independent component.

3.1.1 Smart objects

SO are characterized by their cyber-physical nature, that is, the symbiosis between their physical function and the abstract representation of this function in the virtual space. By complementing their functionalities with more powerful ones operating in the cloud, even resource-constrained objects of the physical world situated on the "edge" of the system such as home appliances become digitally accessible and manageable (Karnouskos, 2014). SO are uniquely identifiable, localizable, and capable of interacting with each other and humans (Minerva et al., 2015). As a particular characteristic of Industry 4.0, advanced data mining algorithms are integrated within SO as dispersed parts of the system, facilitating distributed big data analytics (Leitao et al., 2016). This enables SO to perform complex autonomous acts, i.e. to realize self-x properties such as self-learning or self-healing.

3.1.2 Cloud-based Internet of Things and Services

SO interact with each other or with humans through the "self-configuring, adaptive, complex network" (Minerva et al., 2015) of Internet of Things (IoT). In Industry 4.0 IoT is coupled with Internet of Services, i.e. ability of service providers to offer their services via Internet (Hermann et al., 2016). In this way, a shift occurs from IoT as a network that connects end-user devices to Internet of Things and Services (IoT&S) as a network that connects physical objects and humans - customers and providers - in order to offer particular services. Utilization of cloud computing - paradigm in which services such as computation, storage, and network are offered on demand over the internet - leads towards a cloud-based IoT&S, enhances cloud-centric interactions, and brings even more flexibility and connectivity into industrial systems (Karnouskos, 2014).

3.1.3 Smart grid

SG are "power networks" that intelligently integrate the behaviors and actions of all stakeholders connected to it" with a goal to "efficiently deliver sustainable, economic, and secure electricity supplies" (Alahakoon and Yu, 2016). The key building block of a SG is the Advanced Metering Infrastructure (AMI) which enables deployment of smart meters (SM) at end user points, and allows bi-directional communication of fine-grained monitoring data captured by SM both within SM utility, and among SM utility and the cloud. Integration of AMI in utilities such as homes transforms these utilities into smart, partially autonomous, sub-systems where SO interoperate to provide optimized energy control.

3.1.4 Humans in-the-loop

One of the key purposes of the SG architecture is to enable real-time decision making based on real-time or "active" data that is harnessed from SM and other SO. Humans in-the-loop, a so far not sufficiently addressed component of Industry 4.0, requires taking into consideration questions such as of their application domain, operations performed, and type of data exchanged with the system (Leitao et al., 2016). Furthermore, it brings to attention the questions of human-machine interaction and role of human knowledge. Key stakeholders in SG make management decisions, regarding, for example, energy trading, managing customer relationships, grid infrastructure optimization, or energy management.

3.2 Operational mechanism

Insights obtained from the literature review form the basis of the model. Information about the domains comes from the NIST classification (Greer et al., 2014). We describe how interactivity of actors, i.e. entities which perform knowledge-based activities (humans, SO, and computational systems embedded in the cloud), enables data and information flows, and emergence of knowledge. Interactivity in SG occurs vertically, i.e. cross-level within the levels of the enterprise system and horizontally, i.e. cross-domain through dispersed value networks. However, by building on concept of *Ba* (Nonaka and Konno, 1998) here we consider interactivity more as a precondition of knowledge emergence. Namely, as occurring not in a pre-given three-dimensional space yet as an ongoing, nonlinear process occurring in a "topological space the network of interactions recursively create" as a whole, which requires human (Kakihara and Sørensen, 2002). Thus, in our model (Figure 3), whereas data and information can be automatically processed and can flow through the virtual and physical systems, knowledge emerges only through the involvement of the human systems in the mental layer.

Conceptual models are simplified representations of target systems. Hence in the mental layer we consider only the human-machine interaction through user interfaces and not human-human interaction. Furthermore, in giving examples of interactivity, we focus on only one aspect of SG dynamics – demand side management activities, aiming to keep supply and demand in balance.

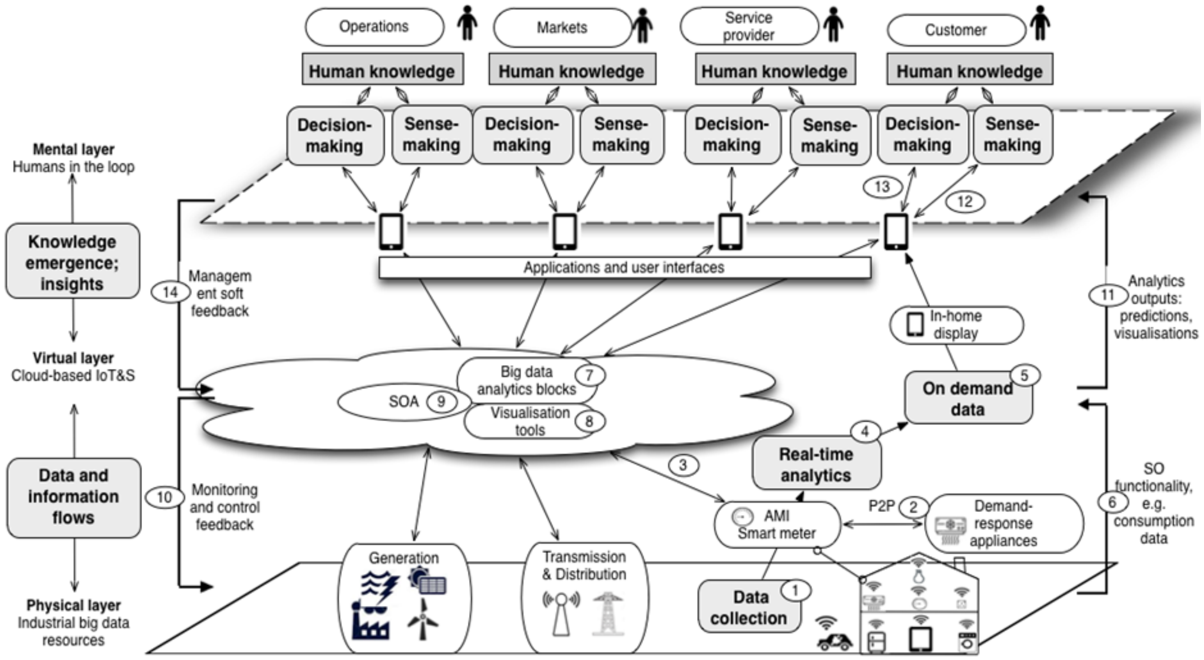

Figure 3 Knowledge dynamics in Smart Grid scenario

3.2.1 Physical layer

SM collect contextual consumption data for the whole smart home household (1). They share data and information bi-directionally and wirelessly both in P2P manner (2) and via Cloud-based auxiliary services (3). They can control and manage energy consumption of smart appliances, such as air-conditioners. Data that they capture locally is processed in real-time (4). Data analytics activities initiated by AMI are mostly data-driven, e.g. cluster analysis, which utilize consumption data to generate consumption patterns and to identify typical customer behavior, i.e. load profiles (Alahakoon and Yu, 2016). They can provide their functionality, e.g. consumption data, as a service in a standalone mode; these data can on demand (5) be displayed to the consumers via in-Home displays (IHD). SM, furthermore, encapsulate their functionality – in a form of data and information flows – to the cloud for further processing (6). Since they are built by taking into account service-oriented architecture (SOA) principles, they can be integrated with cloud-based SOA. This allows dynamic binding of their functionalities with rule-based workflows defined in the cloud, and therefore dynamic behaviour adaption, based on data feedback they receive. For example, in response to particular conditions such as high pricing and peak periods, bidirectional interaction among SM and the cloud allows remote shifting the time of use of home devices.

3.2.2 Virtual layer

Virtual layer (i.e. a cloud) comprises components such as big data analytics blocks (7), visualization tools (8), and an integrated SOA (9). The cloud stores massive amounts of data and information from SO (physical layer) (6), and business and human-related data and information (mental layer) (14). Here, the application-driven activities such as decision trees and neural networks are used and activated directly by stakeholders and business needs, government policies, or environmental factors (Alahakoon and Yu, 2016). For example, fine-grained consumption data can be merged with environmental and financial data for the purpose of calculating energy impact of business processes, which leads to system-wide optimisations. Furthermore, analytics could be used for setting up dynamic pricing to suit various customer profiles and needs. Since these needs change over time, and depend on factors such as current customer activities or local weather conditions, “in computational terms this translates into an online learning and scheduling problem under uncertainty” (Ramchurn et al., 2012). The analysis results are fed back as data and information to the physical layer for the purpose of monitoring and controlling. For example, when a network part is at a peak, the cloud sends instruction to switch off individual appliances. Furthermore, visualization tools generate customized statistical reports (e.g. load profile) that are fed back to humans (mental layer) who access these reports via various applications. The cloud integrates the physical and mental layer via data and information based feedback loops.

3.2.3 Mental layer

Mental layer constitutes humans-in-the loop who make critical decisions with an aim to support efficient grid functioning and satisfying their own needs. The virtual layer interacts with humans through user interfaces that are integrated in various applications. Humans make sense (12) of incoming data and information provided by user interfaces, make decisions (13), implement their decisions (14) via devices (e.g. regarding consumption management), and receive feedbacks in form of new data and information (e.g. consumption data feedback). These knowledge-intensive activities are governed by humans' tacit knowledge. Since situations evolve, their handling is rather a recurring activity than a single event. The virtual layer provides humans with a better understanding of the physical layer and its impact on business and consumption processes. For example, customers can monitor electricity usage even down to the level of separate appliances, which brings more awareness into their electricity usage behavior. As well, these applications constitute a mechanism to bring customer generated data into enterprise systems. In this way, customers` demands and feedbacks serve as real-time inputs for a more evidence-based decision making. Thus, service providers can profile them for targeted services and higher loyalty.

3.3 CLP application scenario

CLP Power Hong Kong Limited, power generation, transmission and distribution company, has set foundations for SG particularly with an IoT-based smart metering pilot project called "myEnergy Program", which was completed in 2014 in selected residential and commercial areas in Hong Kong. Pilot adopted SM infrastructure to provide novel services focusing on behavior-based demand-respond management aimed at changing customers' consumption behavior and attitudes, i.e. to motivate more conscious and sustainable energy consumption decisions. Customers were able to track progress against goals by setting alerts based on their own consumption patterns, specific lifestyles and preferences. For example, when a defined household electricity threshold was going to be exceeded, customized notes were sent to customer applications informing them that they are going to exceed their usual energy consumption and offering recommendations for smarter energy usage. The pilot gained positive results, with an up to 20% demand reduction in critical peaks. Additionally, data analytics experts were able to better understand consumption usage patterns and to offer new billing and payment options. CLP provides services such as assessing the viability of community solar and Meter Online Service. The latter incorporates features such as "Forecasting the Occurring Time of Peak Demand", which is designed for customers with high chiller consumption, due to ambient temperature and humidity typical for Hong Kong's sub-tropical climate. Thereby, customers can anticipate high consumption days and plan energy savings. CLP is, however, only starting with SG journey, which they perceive as having a critical role in Hong Kong's aspirations to become a sustainable smart city. Namely, Hong Kong is a compact and one of the most densely populated urban cities with diverse energy users, and electricity constituting a major portion of energy consumption. In this perspective, real-time monitoring and management capabilities offered by the IoT, along with close partnership between public and private sector, can have a broader impact to and lead to economic savings and improvement of the quality of living.

4. Discussion

Mass employment of SO results in flows of data and information in dispersed parts of SG. In the complexity of these data - i.e. in heterogeneity of data types and sources, intrinsic semantic associations, or relationship among networks of data - resides its potential value (Wu et al., 2014), which is realized when it is leveraged to enable and support real-time decisions (Alahakoon and Yu, 2016). However, due to emergent property of knowledge, "actionable insights" and knowledge cannot be extracted from data. They can only be co-created in the interplay between human knowledge and data and information generated by machines. This has in turn an important implications on the perception of the meaning, purpose and design of knowledge management systems (KMS). Namely, it requires addressing the tacit components by including users` perspective, i.e. exploring their cognitive and psychological needs and engaging them in the process of understanding and assigning a meaning to data and information that guide their actions (Stenmark, 2002). There is a necessity of further development of human-machine interaction by taking into account "human factors." Possible research venues involve: development of visualization techniques for more effective data representation, semantic-based intelligent user interaction applications, context-sensitive systems that adapt their behaviour to situations, and cloud-based KMS which allow obtaining knowledge demand via easy access to various services on the internet (Gorecky et al., 2014; Liao et al., 2011; Sonntag et al., 2017).

5. Conclusion

The contribution mainly addresses two aspects. First, we reconsider knowledge theories and discuss how differences in understanding of nature of knowledge have not merely important theoretical but as well practical implications. Namely, adherents of the epistemological assumption that knowledge can be formalized might lead to the understanding of organizational systems as information processing artefacts that depend on data availability and the ability of analytical tools to extract value from these data. The assumption that knowledge is an outcome of dynamic and emergent processes of knowing through context-depended human sense-making, on the contrary, necessarily leads to involving the "human factor" in designing knowledge-driven decision making systems. Second, by modelling knowledge dynamics in SG Industry 4.0 scenario, we exemplify how knowledge emerges through interactivity of actors. The exemplified model represents a contribution towards an understanding of the major facets of knowledge dynamics in Industry 4.0.

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