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The Need for Knowledge Modification in Technology Change:
- A Framework to Consider Changes in Domain Complexity, Knowledge and Productivity

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Abstract: This paper researches productivity in relation to domain complexity and the present knowledge capacity in an organizational context. The study is based on five very different case studies. Three studies are conducted in Denmark, Germany, Mexico, and China and are related to knowledge transfer in the relocation of manufacturing facilities. Two studies investigate operation and automation of oil and gas production in the North Sea. The case study method involves semi-structured interviews, surveys, an analysis of historical production data and observations. Based on the findings from the field studies, the paper develops a conceptual framework that management can use for discussions of productivity, development of knowledge, and design of learning programs when considering changes in the complexity of a domain or a change in knowledge.

Keywords: Knowledge modification; technology change; domain complexity; productivity; learning programs.

1 Introduction

Ever since the beginning of the Industrial Revolution, automatic control systems used in manufacturing and production have been important devices for keeping parameters stable under various conditions. Current advanced automated solutions play an important role in the fields of production and manufacturing by supporting the control of a large number of processes during manufacturing (Onori and Oliveira, 2010; Säfsten et al., 2007) to ensure quality and to reduce cost in manufacturing when a human workforce is replaced with robots or other automated solutions. Automated control systems ensure that different parameters (e.g., temperature, pressure, flow, positioning, etc.) can be kept stable and on track.
Figure 1. Simple processes

Figure 1 illustrates a basic perception of the automation of simple processes in which practice-oriented skills such as an operator’s experience (Hislop, 2013; Collins, 2010), also denoted and introduced as tacit knowledge (Polanyi 1962, 1966), is codified and converted into explicit knowledge (data and information) through an externalization process (Nonaka and Takeuchi, 1995). This process can be observed, for instance, when one starts the motor of a modern automobile, where the starting process has been automated. The driver’s attention and tacit knowledge about the correct choke level, accelerator level, idle speed, etc., have been codified and converted into explicit knowledge and stored in a computer program. This control system is now able to start the motor under almost any condition.

We are now at the edge of a fourth industrial revolution denoted as Industry 4.0 (Lee et al., 2015) where automation through the Internet of Things is brought to an even higher level and expected to be self-configured for resilience, self-adjusted for variation, and self-optimized for disturbances (Brettel et al., 2014; Lee el al., 2015; Kolberg & Zühlke, 2015). However, earlier studies of manufacturing technology have found that technology is not absorbed by default but calls for careful planning (Tapiero, 1990). Studies made by Ellström et al., (1996) and Bainbridge (1983) have identified how the “irony of automation” will arise when the level of automation is increased as equipment will be much more difficult to operate in situations of disturbances and malfunctions. This challenge may also be the case within Industry 4.0. Studies by Döös (1997), Patriotta (2003) and Madsen et al. (2008) have identified how operators therefore need to develop abstract ideas of how equipment is functioning, as well as new skills and competencies regarding how to bring equipment and
production facilities back on track. Mayer et al. (2011) concluded that “especially in high-wage countries the level of automation of many production systems has already been taken far without paying sufficient attention to the specific knowledge, skills and abilities of the human operator”. In a EU study of advanced manufacturing and assembly technologies, Bogue (2012) found that human interaction and expert knowledge constituted a major problem, particularly during the ramp-up process of new production facilities where, on average, 60% of the total production time was spent in error identification, location, and recovery. Initial stages of technology display lower productivity and demand about 65% of the cost of a new system.

![Figure 2. Complex processes](image)

The right-hand portion of Figure 2 illustrates the paradox that accompanies increasing complexity. When more automation increases domain complexity, more hardware and software will be implemented, and those additions will be more difficult to operate and maintain and will be a source for greater errors. Therefore, increased domain complexity demands increased explicit knowledge and tacit knowledge and a higher level of expertise, skills and competencies. Prior research demonstrates that new attitudes among employees will even be required for those employees to be able to handle advanced equipment (Cedefop, 2012). Furthermore, when one considers cases of errors, malfunctions, and disturbances, advanced skills will be especially needed in order to maintain high levels of productivity.

As illustrated in the introduction, several studies have investigated the relationship between the level of knowledge and the level of automation (the complexity of a domain).
While the outcome of the relationship – what is perceived as productivity - is of high importance for management, this discussion seems subject only to limited discussion in the journal Production Planning & Control (PPC) and other journals within the field of operations management. For instance through our literature review, a search for “productivity” in the title and for the related term “automation” identified only 6 and 11 papers, respectively, in the PPC and in the International Journal of Operations and Production Management (IJOPM). Interestingly, a search for “domain” in the title produced zero hits. A similar trend was found in our literature review and through searches in the EBSCOhost and Web of Science databases. A deeper investigation illustrated only few papers focusing on this subject. However, by using negative terminology like “clumsy automation” or “awkward automation” many more studies related to the issues related to automation, knowledge, and learning emerged. The journals Human Factors, Assembly Automation, IEEE and WORK: A Journal of Prevention, Assessment & Rehabilitation produced results as did an international conference entitled “Human Factors and Ergonomics Society.” Hence, a clear gap exists in the literature concerning automation/domain complexity, knowledge and productivity particularly within the field of operations management. At the doorstep to the fourth industrial revolution where much more automation is expected, the aim of this paper is to explore this gap through the central research question: How does the level of complexity of a production domain and the level of knowledge (tacit and explicit) influence productivity?

To address this question, a literature review (Section 2) will be presented to identify a theoretical framework for the analyses. Cases and methodology will be presented in Section 3, and findings will be illustrated and analysed in Section 4. In Section 5, a conceptual framework is developed and, in Section 6, a discussion regarding the conceptual framework will be made before concluding (Section 7) and considering further research.

2 Literature Review

The literature review was based on the suggestions by Hart (1998). The first step was a review of relevant textbooks and papers for background information and ideas. Then provisional lists of key vocabulary terms, key authors, and key works were identified through snowballing. Third, a focused search of the journals PPC, IJOPM, Human Factor and Assembly Automation was made. The PPC and IJOPM journals were selected because these...
publications are considered leading journals among our focus areas. No special issues related to the subject were identified in PPC and IJOPM. The search involved keywords such as “productivity,” “automation,” “knowledge,” “technology,” and “domain” when searching in titles and, later, words such as “automation,” “knowledge,” “productivity,” “modification,” “change and manufacturing,” “clumsy automation,” and “awkward automation” were used in different combinations when searching in “abstracts,” “everything,” and “anywhere. The same search was repeated in the databases Web of Science and in EBSCOhost, and collectively a gross list was identified of more than eighty relevant papers. The papers were then examined in relation to the research question, and additional papers were added from an exploration of references and citations. Next, the identified papers were grouped into three major themes: 1) domain complexity - the level of automation, 2) knowledge and automation, and 3) productivity; each theme is further described in the next sections. The three themes were used in grouping and analysis of the findings from the fieldwork.

2.1 Domain complexity - the level of automation

The increasing complexity in engineering design and manufacturing is today considered one of the biggest challenges faced in manufacturing, including the operational level (ElMaraghy et al., 2012). Discussion about complexity and automation has therefore been a fruitful research topic for several decades.

In the 1990s several studies investigated the benefits from Computer Integrated Manufacturing (CIM). The manufacturing industry seems to be less automated than the process industry (Säfsten et al., 2007). CIM, Artificial Intelligence (AI) and Flexible Manufacturing Systems (FMS) have been widely researched. For instance, Tapiero, (1990) concluded that companies could be disappointed by introducing these systems because they were over-estimated and difficult to implement. Mertins and Wiencke-Toutaoui (1991), Gupta & Yakimchuk, (1989), Newmann and Sridharan (1993) and, to some extent Gunasekarna et al. (1993) found that FMS systems should be automated stepwise and include massive training of operators to be able to utilize the automated technology. The lessons learned from the concepts of CIM and FMS resulted in the need for a reduction of complexity through modularization and lean technologies (Zuehlke, 2010). In handling complexity there seems to be a trend towards lean and flexible workforce (Tan et al., 2013), lean and
automation (Bortolotti & Romano, 2012), and studies where Human Resource Management practices are investigated to enhance manufacturing flexibility (Urtasun-Alonso, 2014). Earlier studies (Sheridan and Verplank, 1978; Endsley and Kaber, 1999) and later studies (Fast et al., 2009; Dencker et al., 2009) have investigated domain complexity by suggesting taxonomies. In these taxonomies, humans make decisions and actions at very low levels of automation. Conversely, with high levels of automation, the computer decides everything, acts automatically, and ignores the human. In a study of the automation of navigation tasks, Endsley and Kiris (1995) identified five levels of automation. At the lowest level (level one), no systems were automated, and only humans could decide and act; at the highest level of automation (level five), the system’s role was to both decide and to act without involving humans. Ntuen and Park (1988) developed a similar five-level taxonomy of automation within the context of tele-operations systems, and Endsly and Kaber (1999) developed a ten-level system of automation for use within numerous domains, including advanced manufacturing, air traffic control, aircraft piloting, and tele-operations. During the last decade the Swedish DYNAMO study defined “Dynamic Levels of Automation” as a matrix: composed of (a) mechanical automation, which includes the mechanized and physical aspects of automation, and (b) information and decision automation, which encompasses computerized (cognitive) tasks (Frohm, 2008; Fast-Berglund et al., 2013; Fast et al., 2009).

In an analysis of the models of the different models of levels of automation, Wickens et al. (2010) found that the workload would be progressively reduced when introducing a higher degree of automation. However, Wickens et al. (2010) also identified that when automation fails the human-machine system, performance may be catastrophic. This finding has also been underlined by Onnasch et al. (2014) who identified negative impacts resulting from higher degrees of automation on failure systems’ performance and situation awareness. At the doorstep to Industry 4.0 there seems to be a change as studies (Kolberg & Zühlke, 2015; Gorecky et al., 2014; Schuh et al., 2014) call for much more integration of people and the cyber-physical structure in the future Industry 4.0.

This review of available literature resources will underscore the development of a conceptual framework of domain complexity, knowledge, and productivity found later in this paper.

2.2  **Knowledge and automation**
Benefits of automation tend to occur during routine and low-workload situations that generally do not require intensive knowledge (Bogue, 2012; Almgren 2000). Although automation has led to cost savings and increased comfort and safety, recent studies have identified a need for greater skills when new and advanced technology are introduced into manufacturing (Tapiero, 1990; Co et al., 1998; Prinz et al., 2016; Ullrich et al., 2015). More in-depth focus on Human Resource Management, especially when flexible manufacturing is involved has also been identified (Urtasun-Alonso et al., 2014). Other studies (Fasth-Berglund el al., 2013) have identified that humans and technology have to cooperate in order to simplify a job and to make the overall system more efficient and productive.

Because automation is not always developed logically - and may even be considered “clumsy automation” (Bradshaw et al., 2013) - it will often require new and more extensive knowledge among employees. Earlier studies among airplane pilots (Santer and Woods, 1992) have illustrated that the core system of cockpit automation, the Flight Management System, may be clumsy (Wiener, 1989) in a situation that requires extra cognitive work and exacerbates bottlenecks during busy, high-tempo, high-criticality, event-driven operations. Similar results can be found within manufacturing and will particularly emerge in the ramp-up phases of a new production (Bogue, 2012; Almgren, 2000). Within a study of automation of nuclear power plants, Smith (2012) found that when people are not properly trained to respond to new events or they do not do so regularly, they would not be able to act under pressure. At nuclear power plants this situation may end up in catastrophe beyond the control of the operators, designers, or engineers (Schmitt, 2012).

Earlier studies (Endsley and Kiris, 1995; Parasuraman et al., 2000) have found that a high level of automation will lead to skills degradation and loss of situational awareness. Operation of highly automated equipment is also found relatively easy during normal operations (Madsen, 2009); temporary workers (Tan et al., 2013) can even carry it out. However, knowledge of how to solve malfunctions, disturbances, and/or breakdowns of advanced manufacturing facilities, including a high level of automation and extensive codified knowledge will call for “hidden knowledge” (Madsen et al., 2008) of “high viscosity” (Davenport & Prusak, 1998). Madsen et al. (2008) found that solving this kind of “operation with disturbances,” “systemic breakdown,” or “bricolage” calls for an advanced number of skills, experiences, and attitudes among employees at both the individual level and on the
group level. Therefore, disturbances and malfunctions in a highly automated manufacturing environment require the use a broad spectrum of knowledge and more holistic models (Patriotta, 2003; Madsen, 2009; Döös, 1997). In particular, employees require knowledge and skills-based, rules-based, and knowledge-based knowledge to solve these kinds of problems as they occur (Dencker et al., 2009). The more complex tasks mentioned above have to be carried out by permanent workers who have completed training and learning programs that are much more extensive (Tan et al., 2013).

Earlier studies identified that very few technology changes gain instant acceptance among employees because automation can be disused, misused or abused (Parasuraman & Riley, 1997). However, several years later Parasuraman and Manzey (2010) found that through adaptive automation, additional and well-defined human-automation interaction benefits could be achieved in balancing workloads and maintaining situational awareness.

Thus, there seems to be a paradox in the required knowledge related to level of automation. On the one side, automation can improve routine jobs, which are not particularly knowledge intensive. On the other side, a high level of automation calls for more skills and a broader field of knowledge among employees, which is necessary in cases of malfunction, disturbances, and when automation is not developed perfectly, (often denoted as clumsy automation).

2.3 Productivity

Productivity has been discussed as long as the industry itself. Although there have been various definitions and modifications, productivity is still a question of the relation between input and output (Mathur et al., 2012).

The challenge of achieving benefits from advanced manufacturing technology has been identified in German studies where managers at 36% of the participating companies explained that they had experienced exaggerated automation solutions (Lay and Schirrmieister, 2001). Within the car manufacturing industry, for example, Toyota has experimented with technically sophisticated production lines at their Tahara plant through their development of the Toyota Production System/lean manufacturing (Benders and Morita, 2004). However, Toyota experienced only marginal benefits in output due to development and maintenance issues pertaining to the sophisticated equipment (Benders and Morita, 2004). Similar findings occurred at Volkswagen AG (VW) (Gorlach and Wessel, 2007) in a
comparison of the levels of automation at their German and South African sites. In the VW study, Gorlach and Wessel (2007) found that in terms of quality and cost, plant locations and automation (or de-automation) at VW need to be considered in relation to employees’ levels of education, skills, and motivation. The focus on lean manufacturing seems to underline this argument, as lean manufacturing and lean in service generally focuses more on humans and less on automation (Coffey and Thornley, 2006; Benders and Morita, 2004; Bortolotti and Romano, 2012).

The most commonly used measure for labour productivity is output per hour of work (Steindel and Stiroh, 2001). Within operations management, a broader perspective is often used to measure productivity, one typically described by the equation of output from operations divided by input to operations (Slack et al., 2013). Because of the number of different processes in modern manufacturing, the measurement known as Overall Equipment Effectiveness (OEE) has become increasingly popular and widely used (Muchiri and Pintelon, 2008). OEE integrates different and important aspects of productivity in manufacturing, including production efficiency, maintenance effectiveness, and quality efficiency into a single measurement tool.

When developing the framework for discussion of productivity in relation to change in knowledge and/or change in the complexity of domain, similarities were found between very different fields. We have therefore created an index of productivity in relation to time (months), so the framework may be applicable to a number of different contexts.

2.4 Literature review – summing up
Findings from currently available literature demonstrate that there have been several studies on the appropriate level of automation. Scholars in the field of automation are typically denoting this focus area as the complexity of a domain. The discussions of automation within manufacturing and the field of operations management seem to decrease particularly in the PPC and IJOPM journals throughout the last decade. Approximately 2/3 of the identified papers that focus on automation and manufacturing originate from the 1980s and 1990s when the primary perspective on automation considered FMS and CIM. More recent discussions of challenges related to automation were identified to be less in focus in the operations
management literature but in focus in the literature concerning human factors where clumsy and poor developed automation developments were discussed.

The relationship between the domain complexity/level of automation, knowledge among employees, and the output seems limited in the current research. This relationship is addressed in this paper.

3 Cases and Methodology

Five very different cases were carefully selected to maximize the utility of information and to establish a well-defined slate of expectations about their information content (Flyvbjerg, 2006; Yin, 2009; Voss et al., 2002; Swanborn, 2010). The diversity of this selection allows a full investigation into the relationship between domain complexity, knowledge, and productivity in very different contexts. Three cases (A, B, and C) concerned relocation of manufacturing facilities, and in each of these three cases, the main focus was on transfer of knowledge and development of knowledge to ensure high productivity. Cases B and C allowed us to study knowledge, learning aspects, and productivity in a unique situation where between 95 and 100% of all employees were changed, while technology solutions and equipment remained almost 100% unchanged. In Case A, on the other hand, technology solutions and equipment were simplified. The field studies of Cases A, B, and C were conducted in Denmark and Germany (the sending context) and in China, Mexico, and Denmark (the receiving context). Interviews were conducted at all levels, including blue-collar workers on the assembly line, technicians, and managers in all cases. A decrease in employees, from 800 to 350, occurred throughout our study in Case A because the company, three years after becoming established in China, started an outsourcing process and moved manufacturing of parts and equipment to sub suppliers, keeping only assembling in house. In Case A, therefore, our focus emphasized the assembling. The interview ratio in Case A was 25/800 (before outsourcing) or 25/350 (after outsourcing), so the number of interviews was therefore roughly equivalent to those of Cases B and C. However, as recommended from Grounded Theory (Glaser and Strauss, 1967), the saturation of new information in Case A was achieved after the first 20 interviews, similar to Cases B and C.

Two cases were from offshore oil and gas production (D and E); in these cases, the main focus was on automation of a very complex and constantly changing offshore oil and gas
domain to improve productivity. The field studies from the offshore oil sector (Cases D and E) were conducted at offshore production platforms in the North Sea and at the company’s headquarters.

Table 1. Outline of Cases

<table>
<thead>
<tr>
<th>Case</th>
<th>Produced product(s)</th>
<th>Overview of case</th>
<th>Production methods</th>
<th>Duration of research</th>
<th>Employees</th>
<th>Interviews</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Compressors</td>
<td>Plant moved from Germany to China</td>
<td>Manufacturing of parts and line assembly. Cycle time: 10 sec.</td>
<td>4 years</td>
<td>350 - 800</td>
<td>25</td>
</tr>
<tr>
<td>B</td>
<td>Electric machines</td>
<td>Plant moved from Denmark to Mexico</td>
<td>Automated and semi-automated manufacturing and assembly. Cycle time: 16 sec.</td>
<td>2½ years</td>
<td>100</td>
<td>34</td>
</tr>
<tr>
<td>C</td>
<td>Valves</td>
<td>Plant moved within Denmark</td>
<td>Manual assembly and semi-automated assembly. Cycle time: 60 sec. to 1 hour.</td>
<td>2½ years</td>
<td>120</td>
<td>24</td>
</tr>
<tr>
<td>D</td>
<td>Offshore crude oil production</td>
<td>Daily optimisation + add on projects</td>
<td>Continuous flow production</td>
<td>2 years</td>
<td>100</td>
<td>11</td>
</tr>
<tr>
<td>E</td>
<td>Offshore crude oil production</td>
<td>Start-up of new oil production platform</td>
<td>Continuous flow production</td>
<td>1 year</td>
<td>100</td>
<td>3</td>
</tr>
</tbody>
</table>

The manufacturing cases were chosen because they were found to be “informative cases” and “representative cases” (Swanborn, 2010) and because similar trends were identified in the relationship between domain complexity, knowledge, and productivity from the very different cases within the oil and gas sector and the cases within manufacturing. Therefore, a cross-analysis (Eisenhardt, 1989) of patterns could be made within the very different contexts of manufacturing and production in the offshore oil and gas sector. With these five different cases, we were able to make a multiple-case study (Yin, 2009; Voss et al., 2002; Swanborn, 2010) and thus to achieve different perspectives on the phenomenon. The case study method (Yin, 2009; Voss et al., 2002; Denzin and Lincoln, 2011; Eisenhardt, 1989)
was also chosen because it is considered as a powerful research method appropriate to the exploration of a complex setting requiring deep insights into case subjects (Eisenhardt, 1989; Swanborn, 2010, Flyvbjerg, 2006).

The whole case study research process featured an explorative and integrative approach inspired by Maaloe (2002). This research approach was further developed and illustrated in Figure 3. 1) First, similar trends of the relationship between domain complexity, knowledge, and productivity were found from pilot research in different fields of: a) relocation of manufacturing units and facilities and b) automation of complex production of offshore oil installations. Several summaries and papers were developed and combined through this pilot research. 2) Then, the theory was investigated through a literature review, and gaps were identified. 3) Revisions of the research approach were considered through reflection and adjustments. 4) Drafts, including summaries of the pilot study, were developed. These drafts were initially literature reviews and, later, would typically function in the role of process conference papers. 5) Protocols, including research themes (knowledge, learning, automation/domain complexity, and productivity), interview guides and such, were developed and based on the literature study, pilot study, research occasions, and drafts were compiled. 6) Fieldwork, consisting of 97 semi-structured interviews (including 17 focus group interviews), was completed. Careful field notes were made when observing in the field, and almost all interviews were taped, summarized, and approved. In all cases, surveys were made of codified knowledge embedded in documents such as standard operational procedures (SOPs), work instructions, maintenance instructions, data of production, etc. In Cases D and E, the study included a survey of production data of more than 5,000 input/output points where data had been collected over several years. 7) The logbook notes, summaries, datasheet and quantitative data were then analysed for the key content of the relationship of knowledge, automation/domain complexity, and productivity. Through the development of summaries and analysis, the first attempts of Figures 4, 8, 9, and 11 were developed.

In all cases, some of the summaries and analysis led to a further justification of the protocols before the next fieldwork steps (interviews, surveys of data, and measurements) were taken, creating a loop that returns to Steps 3 and 4 (revision and drafts). Because the research was designed to be a longitudinal study, some changes were experienced throughout
the process. This refinement is depicted in the figure as Step 8) pressure from the field, which also led back to Steps 3 and 4, revisions and drafts, before the final paper, 9) could be achieved.

Figure 3. Flow of the study (inspired by Maaloe, 2002)

To increase internal validity through the tracing of cause and effect (Leonard-Barton, 1990), the field studies were carried out in real time as longitudinal studies (Aahlström and Karlsson, 2009). Weeks were spent in each of the case companies making surveys of documents and data and conducting interviews and observations among blue-collar workers on the shop floor and with technicians and management at all levels. Further, several visits were made to the involved plants and offshore sites and followed up through monthly phone calls. Following each of the cases for months, rather than limiting the research design to a single-day case study, resulted in deeper insights and enhanced richness of understanding (Coughlan and Coghlan, 2002). In addition, a number of flow diagrams and features of system layout of control systems were investigated to analyse the domain complexity and explicit knowledge.

4 Findings and data analysis
Table 2 below illustrates an overview of the main findings related to change of domain complexity, change in knowledge level (explicit and tacit knowledge), and change in productivity.

**Table 2. Outline of Findings from Cases and Learning Programs**

<table>
<thead>
<tr>
<th></th>
<th>Case A</th>
<th>Case B</th>
<th>Case C</th>
<th>Case D</th>
<th>Case E</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Type of site</strong></td>
<td>Green field site</td>
<td>Green field site</td>
<td>Brown field site</td>
<td>Brown field site</td>
<td>Green field site</td>
</tr>
<tr>
<td><strong>Change in domain complexity</strong></td>
<td>De-automation, simplification of domain – simpler and local Chinese machines were implemented</td>
<td>Unchanged –existing equipment moved</td>
<td>Unchanged –existing equipment moved</td>
<td>Continuous increase in domain complexity by adding on new equipment</td>
<td>Increased domain complexity through start-up of new unproven facilities</td>
</tr>
<tr>
<td></td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td><strong>Change in knowledge level</strong></td>
<td>Lower Start-up of new plant, 98% of all employees were new at new site in China</td>
<td>Lower Start-up of new plant, 98% of all employees were new at new site in Mexico</td>
<td>Medium Plant was merged into existing plant but 95% of all employees were changed in five months</td>
<td>Increased Skilled operators who constantly were in job training through handovers</td>
<td>Unchanged Knowledge generation as needed</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Focus on learning programs, development of new skills and competencies</strong></td>
<td>Low Focus on very simple tasks where cycle times were down to 12 sec.</td>
<td>Low-Medium Focus on following Standard Operations Procedures (SOPs)</td>
<td>High Extensive learning programs</td>
<td>High Extensive learning programs</td>
<td>Low No focus on learning programs</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Change in Productivity</strong></td>
<td>Unchanged productivity after relocation</td>
<td>Decrease Serious fluctuation and between 30% and 50% from what was expected</td>
<td>Increase + 50% gained the first year</td>
<td>Unchanged productivity</td>
<td>Lower 25% lower production than estimated</td>
</tr>
</tbody>
</table>
Findings concerning learning programs are also included in Table 2, because learning is an important aspect of change and development of knowledge as identified by Dencker et al., (2009) and Forés and Camisón (2011). Detailed descriptions of the findings from our field studies, including graphs illustrating expected and realized output, are illustrated in sections 4.1, 4.2, and 4.3.

### 4.1 Unchanged domain complexity and change in the level of knowledge

In Figure 4, the arrows illustrate the change of knowledge in Cases B and C. In both cases, the starting point “X” illustrates the status of knowledge and the complexity of the domain just before the transfer. However, it is important to note that the level of knowledge and the level of domain complexity were not identical in Cases B and C. Therefore, Figure 4 illustrates how knowledge in Case B decreased after the relocation of the production line and how knowledge increased in Case C after the transfer. Consequently, the equipment and the domain complexity remained unchanged in both cases.

![Figure 4. Unchanged domain complexity](image)

Case B demonstrated a high level of automation (Endsley and Kaber, 1999; Fast et al., 2009), as well as the “irony of automation” (Ellström et al., 1996; Bainbridge, 1983). In Case B, a highly automated production line was moved, without changing the equipment, from Denmark to a new plant established on a green field site in an industrial area in Mexico. The manufacturing facilities constituted a complex domain and included advanced manufacturing equipment, including four robots, CNC machining, automatic welding, automatic testing, and
automatic decision making of parts picking etc. Tacit knowledge in the sending context, such as skills, experiences, competencies and attitudes, had been building up among the Danish employees for twenty years on the individual and group levels. Management planned for a fast ramp-up of production in the receiving Mexican context and expected 100% output within four weeks after the transfer. Therefore, the automatic control systems, which included explicit knowledge, were improved and tested to ensure reliability before the move to Mexico.

Managers had a strong focus on explicit knowledge and standard operational procedures (SOPs), but they found they had neglected the development of skills and competencies among their employees through learning programs.

![Figure 5. Productivity (Case B)](image)

Figure 5 illustrates the fluctuation in productivity between the planned and the actual outputs through the first 4½ months and the area between the planned and actual production can actually be regarded as a loss. As seen in Figure 4, the neglected focus on learning programs depicts a drop in knowledge while the complexity of the domain was kept unchanged (equipment was unchanged). The exchange of 98% of current employees for new hires resulted in a lack of group knowledge and made it difficult for the new employees to work together as a group. For instance, as one Danish training team member in a focus group
interview observed, “Most of the new employed women in the production were divorced and alone with a child or two and had so much they should talk about before they were ready to learn and could start working together.” The identification of causes that led to disturbances, malfunctions, and problem solving of equipment was extremely time-consuming on the shop floor. For example, the production manager explained how “the identification of a periodically loose earth connection on an automatic welder sometimes made one of the four torches to fail and it took us weeks to locate and to solve that simple malfunction.” While the complexity of the domain was unchanged, the decrease in knowledge led to only 40% of the expected productivity, as well as scrap rates above 20% in the ramp-up phase. During the phases of ramp-up, top management realized that anticipating full production after only four weeks was far too ambitious; consequently, they called for significantly more training, education, and learning programs among the new employees.

In Case C, the domain complexity was also unchanged but knowledge was increased through intensive learning programs. This increase is illustrated in Figure 4, where the starting point “X” identifies the knowledge level before the transfer, and the upward vertical arrow illustrates how knowledge was developed during the first year while the complexity of the domain remains unchanged. In this case, a whole plant, including manual and semi-automated equipment, was moved to a new location within Denmark and merged into an already existing plant. This brown field site was chosen because Company C wanted to gain advantage of large-scale production in the receiving plant. Ninety-five percent of all 120 employees were exchanged with new employees within a few months. Extensive training and learning programs were developed and carried out on the individual level among all new employees. In addition, collective learning programs, e.g., the introduction of daily white board meetings, training sessions in assembling valves, and training sessions on how to use the ERP (Enterprise Resource Planning) systems were accomplished in the whole organization.

Figure 6 below illustrates how Case C was able to increase the productivity through
Figure 6. Productivity (Case C)

these training and learning programs where new collective attitudes were developed in the company, and productivity increased 50% within the first year. In addition, the plant was able to meet a 20% increase in sales. Two years after the relocation, the responsible manager explained, “Now changes have just become a normal collective attitude on the shop floor.”

4.2 Unchanged knowledge and change in the level of domain complexity

In Figure 7, the findings from Case E illustrate the effect of changes in the complexity of the domain when there is no change in the level of knowledge. As in Figure 4, the “X” illustrates a starting point; in this case the starting point indicates a normal and standard offshore oil field. In Case E, new oil production facilities were established on a marginal oil field where production was very complicated. Very little effort was made to develop knowledge for operations, since knowledge acquisition and training in the offshore oil sector often requires a number of extra exploration wells, and marginal reservoirs may increase costs dramatically. Figure 7 depicts the oil production profile for the first 12 months of a new field (Nini East field). The Nini East field consists of thin sandstone reservoirs giving the production profile. Sandstone normally makes high oil inflow rate possible, but because the reservoirs at Nini East are thin, the drain of oil can only be high in the early phase and then needs to be reduced after a few months to avoid water breakthrough. As illustrated in Figure
7, the production rates had to be reduced after 4 to 5 months and the planned peak production was never achieved in Case E.

![Production Graph](image)

**Figure 7.** Nini East production (Case E)

Case E therefore illustrates an instance where knowledge of how to operate this oil production field was unchanged but the domain complexity was increased dramatically when compared to production from other oil fields. Consequently, the production from this oil field (Case E) was much lower than the predicted oil production.

Through our study of the literature concerning domain complexity, automation, knowledge and productivity, we have observed that lean manufacturing focuses less on automation and more on standardizing processes to reduce waste (Benders and Morita, 2004; Coffey and Thornley, 2006; Bortolotti and Romano, 2012; Bicheno, 2004; Womack et al., 1990). In Figure 8, the lean manufacturing perspective is illustrated as a process in which the level of the domain complexity is reduced while knowledge is kept at a stable level. Some may argue that the knowledge level may increase through a process of implementing lean manufacturing. However, the study of lean manufacturing literature finds that lean manufacturing is more a question of systematizing knowledge within a company and a process wherein tacit knowledge among employees seeks to be codified and converted into explicit knowledge. The knowledge level is therefore illustrated to be unchanged in relation to lean manufacturing. Through case studies, we have not been able to include studies where
only lean manufacturing programs have been the focus. Thus, in Figure 8 the brackets of Lean Manufacturing are used to illustrate what was drawn from the literature.

Figure 8. Unchanged knowledge

4.3 Productivity unchanged—Change in domain complexity and knowledge

In Case A, the manufacturing of compressors was moved from Germany to a new factory built on a green field site in China. In the German plant, the equipment represented a relatively high domain complexity and included a high level of automation. Therefore, the German site required few, but highly skilled, labourers. The company had earlier made an unsuccessful relocation of manufacturing facilities from Germany to Mexico. When moving the complex technology to Mexico, the company faced a number of problems. The production failed to perform in the Mexican context, and two years later the equipment and production were transferred back to Europe. However, six years later, an expanding Chinese market and an opportunity for cost reduction motivated a move to China. This time, an extensive downgrading of the complexity of equipment was made by purchasing local Chinese machines and equipment, which were much simpler to use but required more labour. Managers found the downgrading of the complexity of equipment a good fit. Despite the fact that a large number of new Chinese employees had little tacit knowledge (skills, experiences, competencies, and attitudes) of how to operate manufacturing equipment, tasks on the production lines were carried out through cycle times as low as 12 seconds. Within three years, the Chinese plant grew from zero to 800 employees with no decrease in productivity. Although the company suffered a 20% turnover rate among blue collar workers and a 7% turnover rate among white collar workers and management in Case A, top
management found the simplification of equipment extremely successful, illustrated by the responsible vice president, who explained in an interview, “We have never experienced so positive results from a transfer in the company’s history.”

In Figure 9, Case A is illustrated by the arrow pointing from the starting point down to the left, showing first the reduction of the complexity of the domain and then the decrease in the level of knowledge, which occurred through simplifying tasks in the plant. However, when comparing the productivity from the Chinese and the German plant, the productivity remained unchanged.

![Figure 9. Productivity unchanged—change in domain complexity and knowledge](image)

In contrast to Case A, Case D illustrates a context in which both the domain complexity and the knowledge of production constantly increased. Case D is based on the Siri oil field, which is located in the Danish sector of the North Sea and consists of a number of marginal reservoirs. Oil production from these oil reservoirs is very challenging, as production involves a number of vertical wells and even horizontal wells in very thin sandstone layers at depths of 2,000 meters. In addition, the reservoirs have matured and changed over time, which is an intrinsic cause of increasing complexity. Installations in Case D have experienced ongoing development with a series of add-on projects, which has also added to the complexity. The complexity of the domain was expected to increase during the 20 years of operations planned for the field and lately the lifetime of the field has been extended to 26 years. In Case D, skilled offshore control room operators worked in twelve-hour shifts, two weeks on duty followed by three weeks off duty. These working conditions made knowledge
sharing very difficult within the group of control room operators and the whole organisation; the working environment called for intensive handover procedures to keep operators updated with adequate knowledge of operation. Figure 9 illustrates how, in Case D, the domain complexity increased over time due to maturing reservoirs. Intense peer-to-peer learning and mentoring programs were continuously employed, resulting in an increase in the level of knowledge and avoiding a drop in productivity, as seen in Figure 10. The data set is anonymized to retain confidentiality.

![Graph showing the production of Siri oil (Case D)](image)

**Figure 10.** Siri oil production (Case D)

### 5 Development of a conceptual framework

Based on the literature study, on the findings and on the analysis of the five cases illustrated in Figures 4, 8, and 9, the conceptual framework illustrated in Figure 11 has been developed. The purpose of the framework is to support managers who are considering productivity in situations where the complexity of a domain has to be changed and/or if a change in knowledge has to take place.

As a first parameter, the level of the complexity of a domain is illustrated as the horizontal axis. This parameter is based on our introduction and our literature study in which levels of automation were discussed and the term “domain complexity” was identified to cover a broader spectrum of processes and technologies within automation. The second
parameter, “knowledge” (vertical axis), covers both explicit knowledge (data and information) as well as tacit knowledge (skills, attitudes, and experiences) on the individual and collective levels. The three dotted and sloping lines illustrate three levels of productivity: “higher productivity,” “no change in productivity,” and “lower productivity,” respectively. There may be more than three levels of productivity, and there may be different gradients of the curve for productivity. However, three levels of productivity and only one gradient tendency have been illustrated to keep the framework as simple as possible, thus leaving it up to the user to develop customized curves and gradients for productivity.

![Diagram of domain complexity and knowledge related to productivity](image)

**Figure 11.** Domain complexity and knowledge related to productivity

The centre of the framework in Figure 11 features an “O”, which represents a starting point, and the six numbers (1 to 6) in the figure illustrate different situations and directional arrows based on our findings.

**Arrow 1: Unchanged domain complexity, increased knowledge, and higher productivity.** In this instance, intensive learning programs are needed at both the individual and collective levels, but the domain complexity is unchanged. This situation is based on our study of Case C, where an entire plant employing 120 individuals was moved to a new location and 95% of all blue- and white-collar workers and managers were replaced within five months. In this situation, intensive learning programs to improve tacit knowledge (skills, attitudes and
competencies) among individuals and groups of employees will be required. Intensive activities to improve explicit and codified knowledge will also be needed, such as upgrading documentation, descriptions, and so forth to have standardised knowledge accessible to employees.

Arrow 2: **Increased domain complexity, increased knowledge, and unchanged productivity.** The domain complexity in this instance is constantly increasing, requiring an intensive development of explicit and tacit knowledge, accomplished by upgrading documentation and providing rigorous learning programs to develop tacit knowledge on both the individual and the collective levels. This situation is based on our study of Case D, where skilled offshore control room operators were overseeing and operating the production of oil from the different oil reservoirs the Siri field in the North Sea. Case D included a series of add-on projects, constantly creating new production scenarios, which resulted in a more and more complex production domain. However, rigorous learning programs, mentoring, and systematic peer-to-peer training and upgrading of documentation serve as important models in this case to maintain productivity.

Arrow 3: **Unchanged knowledge, increased domain complexity, and lower productivity.** Arrow 3 illustrates how this study has identified that productivity will decrease if the domain complexity is increased without increasing the level of knowledge in the context involved. Through our field studies, we identified this situation in Case E of the oil and gas production from the Nini East reservoir in the North Sea. Production from this reservoir started in February 2010 and when its domain complexity increased, but no learning programs among employees were developed, productivity suffered.

Arrow 4: **Unchanged domain complexity, lower knowledge, and lower productivity.** Through our fieldwork, this situation was identified to take place in situations where new and unexperienced employees are hired. Case B illustrated these circumstances clearly. The company’s equipment remained unchanged when they moved to the new location in Mexico. Even though the level of explicit knowledge was improved by upgrading and codifying knowledge, the change of 98% of all employees led to an obvious lack of tacit knowledge both on the individual level and on the group level at the new Mexican site. In this situation, the development of knowledge to handle situations of disturbances and malfunctions
(Madsen et al., 2008; Patriotta, 2003) will be an important factor; otherwise, an extreme drop in productivity will take place.

Arrow 5: Simplification of domain complexity, decrease in knowledge, and unchanged productivity. From our study of Case A in Germany and China, we identified how top management had seriously reflected on the unsuccessful transfer of highly automated manufacturing equipment from Germany to Mexico and back again. However, a growing Asian market and a need for cost reduction motivated the decision to relocate manufacturing facilities from Germany to China. A careful downgrading of the complexity of the equipment ensued, through purchasing local Chinese manufacturing equipment that focused on simplicity and human operation rather than automation. The de-automation through downgrading of the complexity of the equipment in Case A made the company able to sustain the same productivity even though the new employees were exhibited very little tacit knowledge (skills, experiences, competencies, and attitudes) among themselves and as a group about how to operate the manufacturing equipment.

Arrow 6: Simplification of domain complexity, unchanged knowledge, and higher productivity. As described in Section 4, no evidence was found for this instance through our studies in the field. However, by studying literature on lean manufacturing (Bicheno, 2004; Womack et al., 1990; Coffey and Thornley, 2006; Benders and Morita, 2004; Bortolotti and Romano, 2012), we noticed how lean manufacturing focuses on simplification of manufacturing equipment, clarity, good layout arrangement, and manageability. In a manufacturing environment, this focus on simplification will therefore imply a decrease in domain complexity, and while knowledge may be unchanged, an increase in productivity may be expected.

From the very different findings from our field studies, we have developed a conceptual framework in Figure 11, which illustrates how productivity corresponds to the level of knowledge and to the complexity of a domain. In the next section, the framework will be discussed in relation to the literature.

6 Discussion

Figure 1 illustrates how knowledge in relatively simple processes can be converted from tacit knowledge into explicit knowledge through “externalization” and by refining explicit
knowledge through a “combination” process (Nonaka and Takeuchi, 1995). However, as illustrated in Figure 2, “the irony of automation” (Ellström et al., 1996; Bainbridge, 1983) appears to arise when automating facilities to a higher level, where operators need to develop abstract perceptions of how to handle technology, particularly in the case of disturbances and malfunctions (Döös, 1997; Patriotta, 2003; Madsen et al., 2008). This approach is a particular focus of this study. Even though the manufacturing industry seems to be less automated than the process industry (Säfsten et al., 2007) the increased complexity in engineering design and in manufacturing is still today considered as one of the biggest challenges (ElMargahy et al., 2012). Zuehlke (2010) therefore found the challenges of complexity from the earlier CIM and FMS lead to a focus on lean manufacturing. This study has identified how a lack of knowledge leads to losses in production illustrated as the area between the “planned” (dotted lines) and the “actual” (full line) in Figures 5, 6, 7, and 10 and ultimately to longer payback on investments. Based on our findings from the field studies, Figures 4, 8 and 9 illustrate a conception of the relationship between knowledge, the complexity of a domain, and productivity. The three figures are merged into a comprehensive framework as illustrated in Figure 11. The three major elements within this framework contribute to the exciting literature and will be discussed in the next sections.

6.1 Domain complexity and productivity

If the domain complexity increases without any change in explicit knowledge or tacit knowledge - that is, without improving skills, experiences, and attitudes among operators through learning programs - as evidenced by our findings, trends toward a drop in productivity were identified. Earlier studies by Patriotta (2003), Döös (1997), Madsen (2009), and Ellström et al. (1996) emphasized the importance of developing tacit knowledge through learning programs to develop employees’ competencies to be able to handle sophisticated technology, particularly in cases of disturbances and malfunctions. Although equipment within the Industry 4.0 is expected to become self-configured for resilience, self-adjusted for variation and self-optimized for disturbances (Brettel et al., 2014; Lee et al., 2015; Kolberg & Zühlke, 2015), the technology of today and in future Industry 4.0 is expected to call for much more education (Kagermann, 2013; Spath et al., 2013). The performance of highly automated equipment is simply found to be catastrophic when automation fails (Wickens et
al., 2010; Onnasch et al., 2014). However, the relation to productivity is missing in the existing literature.

On the other hand, a simplification of technology in our study, or what we have denoted as a decrease in domain complexity, was identified to improve productivity. Lean manufacturing also seems to focus on this simplification (Bicheno, 2004; Baudin, 2002; Coffey and Thornley, 2006; Benders and Morita, 2004; Tan et al., 2013). To be able to keep productivity at a high level, both Cases A (the China case) and B (the Mexican green field case) underscore the importance of not using excessively complicated technology when transferring manufacturing facilities to organizations where tacit knowledge may be limited.

### 6.2 Knowledge and productivity

Through our field studies, we observed that management, especially in manufacturing companies, had a high focus on standard operational procedures (SOPs) when relocating manufacturing facilities but neglected to focus on the development of learning programs to develop skills, competencies, and attitudes among individuals and groups of employees. However, as illustrated particularly through our findings in Case C, an early change in this perception and a strong focus on learning programs were key factors in being able to raise productivity 50% after the first year of relocation of manufacturing facilities (Arrow 1 in Figure 11). The study by Urtasun-Alonso et al. (2014) emphasises the importance of advanced HRM practices in flexible manufacturing and recent studies by Prinz et al. (2016) and Ulrich et al. (2015) have illustrated a need for much more skills when new and advanced technologies are introduced into manufacturing. However, these studies have not identified significant mean difference in education and training investments. In this relation, our study illustrates the importance of education and training to improve productivity and adds to the existing body of relevant literature.

On the other hand, Case B demonstrated a high level of automation (Endsly and Kaber, 1999; Fast et al., 2009) and to some extent an “irony of automation” (Ellström et al., 1996; Bainbridge, 1983) where the automation of equipment was developed through many years of operation in the sending context. Managers in Case B found it very difficult to bring productivity back on track in the case of malfunctions, particularly when almost all
employees were exchanged after relocating the manufacturing facilities to Mexico. Therefore, Case B demonstrates how a decrease in knowledge when operating unchanged manufacturing facilities will lead to a drop in productivity, as illustrated by Arrow 4 in Figure 11. In our study, Case B demonstrated the importance of supporting human interaction and knowledge to make a smooth ramp-up of production facilities, as emphasized in an EU study by Bogue (2012) and by Onnasch et al. (2014).

Our study also revealed how strong safety regulations and legislative requirements in the oil and gas sector (Case D) can lead to a focus on learning programs where skills, competencies, and attitudes are constantly being developed and may lead to a steady productivity despite having the domain complexity constantly increase (Arrow 2 in Figure 11).

From a managerial perspective, the gradient for productivity in Figure 11 will be an important discussion among managers when considering changes in the domain complexity or when planning for the development of skills, experiences, competencies, and attitudes through learning programs. We have chosen to illustrate only one gradient tendency but three levels: “higher,” “no change,” and “lower” productivity, respectively. National and/or organizational cultures and experiences may have an influence on the gradient tendency of productivity. The intention of this study was to develop a framework to support management efforts to keep productivity in focus, particularly when considering change in the domain complexity and/or knowledge; the gradient will be important for management to consider when choosing appropriate learning programs. Our literature study confirms that this instance has only a limited range of discussion in the current literature (e.g. Bogue, 2012; Almgren 2000; Coffey and Thornley, 2006; Benders and Morita, 2004; Bortolotti and Romano, 2012) without the development of a managerial framework like Figure 11 where the productivity can be considered in relation to knowledge and the complexity of a domain.

7 Conclusions, contributions, and further research

The world is now at the doorstep to a fourth industrial revolution (Industry 4.0) where automation of manufacturing equipment is expected to be brought to a much higher level as never seen before. In Industry 4.0 equipment is, for instance expected to become self-configured for resilience, self-adjusted for variation, and self-optimized for disturbances
(Brettel et al., 2014; Lee et al., 2015; Kolberg & Zühlke, 2015) which will be much more difficult to overview for humans who operate and have to bring advanced equipment back on track in case of malfunctions and disturbances.

This study and the developed framework (Figure 11) illustrate the importance of implementing training and learning programs to avoid serious decreases in productivity when introducing more automation and more high technology. Through the literature study, this finding was identified to be a main reason why earlier approaches such as CIM and FMS failed. On the other hand, the framework also illustrates how domain simplification can improve productivity and how simplification of a domain requires fewer skills and less competencies among employees, thus resulting in unchanged productivity. From a managerial perspective, the developed framework (Figure 11) can therefore be used by management to consider changes in productivity, learning programs, and in the level of automation and the relationship between these three elements.

The literature review provided a limited number of papers concerning the challenges companies are facing when experiencing a high level of automation (what we perceive as a high domain complexity). Discussion of this issue was not identified in the current literature from the leading journals within the field of operations management but instead in the academic journals where focus is on human factors (e.g. the journals such as “Human Factors,” “Assembly Automation,” “IEEE” and “WORK: A Journal of Prevention, Assessment & Rehabilitation” and the conferences “Human Factors and Ergonomics Society.” This paper and the developed conceptual framework adds to the limited operations management literature by successfully combining automation/domain complexity, knowledge/learning, and linking these concepts to productivity.

The paper has been developed using the case study method. This method is particularly relevant when the combined field is relatively new (Yin, 2009; Voss et al., 2002; Denzin and Lincoln, 2011; Eisenhardt, 1989). However, future research may benefit from a quantitative approach by testing our results and conclusions at a larger scale. For this potential extension, we have formulated the following expected proportions:

1) **Unchanged domain complexity and increased knowledge will lead to higher productivity.**
2) Increased domain complexity and increased knowledge will lead to unchanged productivity.

3) Unchanged knowledge and increased domain complexity will lead to lower productivity.

4) Unchanged domain complexity and decrease of knowledge will lead to lower productivity.

5) Simplification of a domain complexity and a decrease of knowledge will lead to unchanged productivity.

6) Simplification of domain complexity and unchanged knowledge will lead to higher productivity.

In this study, we could have involved a number of other themes such as motivation, incentives from employees, power relations, but at this stage, we determined that these additions could make our results less clear. However, we recommend future studies to test our results and our propositions and to gain more knowledge about the relationships between the complexity of a domain, knowledge level, and productivity. We also recommend that future studies will be able to include some additional subjects such as motivation, incentives, and power relations for further insights.

8 References


Kagermann, H. et al., 2013, “Recommendations for Implementing the strategic initiative INDUSTRIE 4.0: securing the future of German manufacturing industry; final report of the Industrie 4.0 working group”, Forschungsunion.


Polanyi, M. 1966. “*The Tacit Dimension,*” Peter Smith, Gloucester, Massachusetts.


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Dr. Lars Lindegaard Mikkelsen holds a PhD in Software Engineering (2013) from the University of Southern Denmark. In his research, he is particularly interested in the development of software for multi-objective decision making in real-time production systems. He has a broad experience from the maritime sector and the oil & gas industry. Lars Lindegaard Mikkelsen is currently developing full mission training simulators for the oil and gas industry. He has also developed a number of educational and training programs for the maritime and oil & gas industry. Besides his PhD, Lars Lindegaard Mikkelsen has a very diverse educations background by holding a BA in maritime engineering, a BA degree in Electronics Engineering and MSc in Computer Engineering, which he uses in his research and work to challenge production performance.