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Approach for the Development of a Sustainability-oriented Implementation Strategy of Smart Automation Technologies

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Abstract

With respect to the increased demands on sustainability, Smart Automation is a promising solution to realize an improvement of the environmental impact of production systems. However, the majority of companies are limited in their ability and resources to simultaneously install several technologies. Consequently, the selection and prioritization of technologies in terms of implementation strategies with a particular focus on the environmental impact is a major challenge for manufacturing companies. It is therefore the objective to introduce a framework for decision support for implementation strategies for Smart Automation technologies with special emphasis on environmental impact of the measures taken. An integral part of the approach is the identification of appropriate indicators for environmental performance measurement as well as location factors that may influence environmental impacts. In addition, a conceptual framework and an analysis of the net of bilateral interdependencies of the three pillars environmental location factors, Smart Automation technologies, and performance indicators are developed. Subsequently, these interdependencies are transferred to an assembly system using the methodology of hybrid modeling and simulation. Finally, the developed approach is validated in cooperation with a manufacturing company.

Keywords: Sustainability, smart automation, location factors, hybrid modeling and simulation, implementation strategy

1. Introduction

Since the beginning of industrialization, manufacturers have continuously evolved and adapted in response to changing market demands and new technological innovations [1]. Meanwhile, manufacturing companies need to consider environmental impacts [2]. In terms of successfully managing the transformation towards an environmentally sustainable economy, the adoption of Industry 4.0 technologies and principles can serve as a catalyst of establishing sustainable manufacturing [3].

In order to not only increase productivity but also sustainably reduce environmental impacts, the introduction of smart technologies must be intensified to take advantage of the Industry 4.0 technology adoption [3,4]. In this context, Smart Automation technologies describe an intelligent automated production process characterized by the active support of smart products and technologies [5]. However, investments in such technologies require companies to develop suitable concepts for the effective integration into their existing production systems [6]. Since emerging markets are expected to be responsible for about 70% of global economy growth over the next few years to come, special emphasis is placed on China as a representative, taking into account local conditions related to the environment, such as emission regulations, state fundings, and energy-mix [7].

In summary, with reference to the company-specific initial situation, the identification of suitable implementation strategies of Smart Automation technologies in assembly systems with respect to the impact on the environmental

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sustainability by considering the local conditions is an increasingly important challenge in research and industrial practice. The objective of this paper is to propose a methodology for developing a suitable implementation strategy of Smart Automation technologies that is targeted on environmental sustainability. The main research questions raised are how to analyze and model the interdependencies between Smart Automation technologies, location factors and KPIs including environmental perspectives, and how to select the most advantageous Smart Automation technologies for a given production system.

2. State of the art

The requirements and objectives of the methodology to be developed can be characterized as follows.

- To define company-specific situation, environmentally sustainable location factors, characteristics of Smart Automation technologies, and the KPIs.
- To identify qualitatively and quantitatively account for the interdependencies among the influence factors above.
- To derive an implementation strategy of Smart Automation technologies.

Considering the requirements of methodology to be developed, a review of existing literature is conducted that covering the influencing topics of location factors, lean and green manufacturing concepts, as well as performance and environmental impact assessment [6].

The reviewed research approaches for the assessment of Lean Methods primarily addressed the interdependencies with potentials of Industry 4.0 concepts and technologies [8-10], but completely lack the consideration of location factors. In addition, the elaboration of an appropriate implementation strategy as well as the impact of potential measures taken on the environment are not sufficiently considered.

The area of considering the analysis of Smart Automation with a focus on the evaluation of the maturity level of Industry 4.0 applications, however, combines an enhanced focus on the requirements of interdependencies as well as an ideal implementation strategy including the corresponding evaluation [11-14]. Nevertheless, these concepts again miss the consideration of local conditions as well as aspects of sustainability.

Furthermore, the studies reviewed with regard to the role of location factors clearly indicate the mostly isolated viewpoint of the respective discipline and missing link to the other requirements [15-19]. However, this category slightly includes different aspects of sustainability.

The set of approaches that belong to the research area of performance evaluation of operations of production systems again illustrate a specific pattern consisting of focusing on identifying relevant indicators in conjunction with Smart Automation technologies [20-23]. The coverage of other requirements, however, is highly dependent on the type of technology or production system being assessed as well as the industry sector being targeted. Additionally, the important link between the set of indicators identified and the impact on the environment is only partially taken into account.

Finally, the review of studies associated with the assessment of the environmental impact of manufacturing processes clearly highlights that the focus is on identifying appropriate performance indicators in order to evaluate and quantify the consequences of measures taken. In this context, the investigation of interdependencies between both requirements was mostly performed through a qualitative and quantitative analysis. Moreover, the key point of considering emissions as an important dimension of sustainability became clear [24-27]. Nevertheless, most approaches miss a strategy to serve as a guideline for environmental efficiency improvements.

Therefore, the objective of this methodology to be developed is to fully address the listed requirements including a qualitative and quantitative analysis and modeling of the interdependencies between a catalog of Smart Automation technologies, relevant KPIs and identified location factors. Furthermore, the approach requires the consideration of the company-specific initial situation as well as of environmental aspects of manufacturing processes and the impact analysis of implementing certain technologies. In this context, developing an implementation strategy, including the steps of simulation, optimization, and evaluation, of Smart Automation technologies, would be pioneering for academic research and industrial companies to master the transformation processes in a dynamic corporate environment.

3. Methodology

The proposed methodology is structured into four core elements. In the first part, the catalogs of influence factors that are relevant for manufacturing companies are identified and compiled (see Section 3.1). In this context, catalogs of location factors with regard to environmental sustainability, Smart Automation technologies, KPIs, as well as site roles are elaborated. In the second part, based on the identified catalogs of influencing factors, an analysis regarding the interdependencies between the catalogs is performed (see Section 3.2). Subsequently, in the third part, the qualitative and quantitative models are established in order to present the interdependencies based on the hybrid modeling (see Section 3.3). In consideration of the results so far, the last part derives a procedure for determining an optimal implementation strategy for Smart Automation technologies with respect to certain performance indicators for assembly systems (see Section 3.4).

3.1. Identification of the catalogs of influence factors

The objective is to identify and compilate the catalogs of influence factors. It consists of four steps. The first step describes the process of reviewing and analyzing potential location factors from an environmentally sustainable perspective. The second step focuses on selecting a set of relevant Smart Automation technologies for assembly systems. Furthermore, the third step specifies the definition of appropriate KPIs, again with a particular emphasis on the environmental impact. Finally, in order to consider the company-specific initial situation, a catalog of site roles as well as associated key tasks within an organization's production network is designed.

Take the first step identification of the catalog of environmentally sustainable location factors as an example, the concrete approach is illustrated. First, the scope of relevant location factors was outlined and structured based on existing literature. Second, a questionnaire survey was conducted in order to analyze the relevance and importance of each identified location factor among a group of selected participants. Subsequently, a data analysis was performed on the basis of the survey results. Lastly, expert interviews were implemented to modify and verify the output of the previous sub-steps. As a result, a catalog of relevant environmentally sustainable location factors was identified.

Finally, as a result of the identification of the catalogs of environmentally sustainable location factors, Smart Automation technologies, KPIs, and site roles on the basis of literature reviews, questionnaire surveys, data analytics, and expert interviews with a particular focus on China as a representative of a highly dynamic emerging country.

3.2. Interdependency analysis

The objective is to perform an analysis with respect to the interdependencies between the dimensions of the identified catalogs in the previous Section. First, the concept of the typology of site profiles is explained and a reference to the other three key areas is established. Second, the interdependencies between the different Smart Automation technologies are examined. Subsequently, the pairwise analysis of the interdependencies between all three dimensions of the framework is conducted. Lastly, based on the fundamental concept of the typology of site profiles and the identified relations between the different Smart Automation technologies as well as the pairwise analysis of interdependencies between the three dimensions location factors, Smart Automation technologies, and KPIs, the net of bilateral interdependencies was derived, which represents the conceptual framework for the modeling and simulation as Figure 1 shows.

The key figure Environment is based on the two pillars of Direct Energy Consumption as well as Indirect Energy Consumption, which are differentiated with respect to the corresponding CO2-Emissions. Whereas the Direct Energy Consumption accounts for the energy consumption in terms of electricity, the Indirect Energy Consumption is defined by the associated energy flows of the variety of applicable items consumed during the production process. Since the gate-to-gate principle is realized, the impact of raw materials, e.g., during their extraction, transportation, or fabrication is explicitly not considered. Accordingly, a list of potential items that can be categorized into the groups Material (i.e. material scrap, tool scrap), Packaging (i.e. paper, carton), and Liquids (i.e. water, lubricants) was derived based on the review of several manufacturing processes. However, the list is only to be regarded as an example and should always be configured individually for the respective manufacturing process.

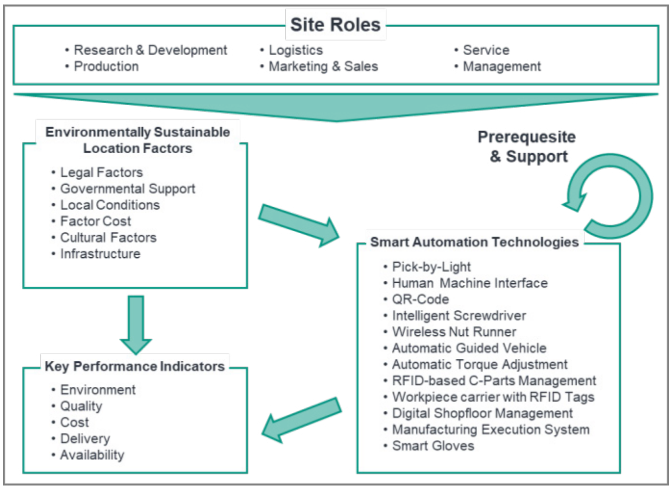

Fig. 1. Framework of net of bilateral interdependencies

3.3. Modeling and simulation

The objective is to develop the model and simulation framework of bilateral interdependencies of a production system, which forms the basis for deriving the implementation strategy for the specific assembly system. The approach is divided into five parts. First, the framework conditions and corresponding requirements for the model are defined as a basis. Subsequently, the concepts of modeling the interdependencies between the different technologies by using the System Dynamics (SD) methodology as well as the production system by using the Discrete Event Simulation (DES) approach are introduced and a hybrid modeling approach based on process data is developed. Lastly, the experiment design is defined accordingly for the simulation. As the result, Figure 2 shows the overall framework of modeling and simulation.

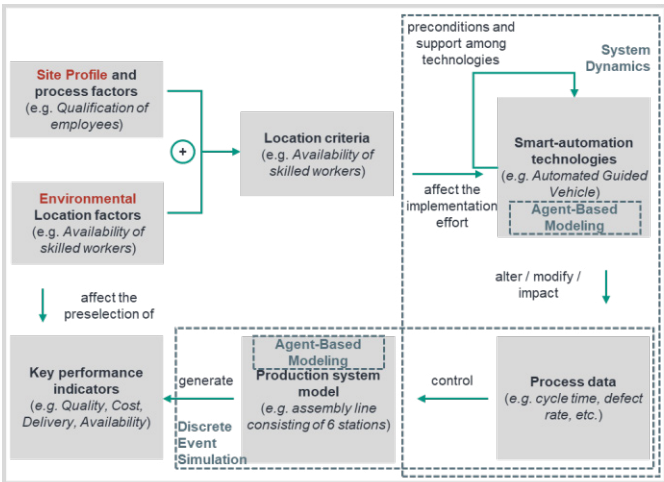

Fig. 2. Overall framework of modeling and simulation based on [7]

3.4. Derivation of implementation strategy

The objective is to carry out the proper implementation strategy of Smart Automation technologies. The key aspects are to first define and describe the company-specific assembly system for the simulation. In order to specify the particular assembly system considered in the simulation, the input data that characterizes the system must be collected. In the context of this work, the input data is composed of five crucial aspects, namely the specific location, the site profile, the current status of assembly process, the initial level of implemented technologies, the relevant KPIs, and the restrictions to be respected.

Second, the procedure of deriving an appropriate implementation strategy is introduced. For this purpose, a deterministic binary linear programming model was developed by [6] to support decision making with respect to the optimal implementation strategy. This model is extended to include the perspective of the KPI category Environment.

Lastly, an approach to evaluate the results of the implementation strategy is presented. Most of the interdependencies identified and quantified in Section 3.2 are based on expert interviews. Accordingly, it must be ensured that the previously determined implementation strategy remains robust and valid in the event of deviations in the data set. A Monte Carlo simulation is conducted to perform the required sensitivity and robustness analysis.

4. Case study

As a first step, the characteristics of the pilot assembly system of the industrial partner are reviewed. Subsequently, the identified interdependencies between the location factors, Smart Automation technologies, and process data are analyzed and discussed with experts from the company with regard to the specific characteristics and requirements of the pilot assembly system and corresponding facility. In this context, the developed simulation model is adjusted in accordance with the specific requirements and conditions identified. Consequently, the simulation is conducted based on the company-specific input data and finally an optimal implementation strategy is formulated and evaluated.

4.1. Review of characteristics and regionalized catalog of pilot system

The pilot assembly system under consideration is located in the Beijing Plant in China, which is part of the production network of a globally operating company. This plant is responsible for the production of hydraulic pumps, motors, and transmissions. In the context of this work, a fundamental part of the Beijing Plant's strategy is to become a leading user of Industry 4.0 applications and solutions.

Based on the results of Section 3.1, the identified catalogs were discussed with two experts with different professional backgrounds from different departments of the Beijing Plant in order to verify the relevance of each element. The experts agreed that a special emphasis should be placed on the KPI Environment. This focus is due to strict regulations in the Beijing area, which require a reduction of CO2-Emissions for environmentally sustainable reasons. In addition, the plant recently established an energy efficiency team with the objective to gradually reduce emissions until it reaches the state of a net-zero emission production facility. However, the other KPI categories, namely Quality, Cost, Delivery, and Availability, should also be taken into account.

All technologies defined in the catalog of Smart Automation technologies are part of the plant's strategy of becoming a leading user of Industry 4.0 applications and are therefore considered. The entire catalog of location factors defined in the corresponding section is considered in the simulation.

4.2. Review of interdependencies among influence factors

The identified interdependencies are analyzed and discussed with experts from the company with regard to the specific characteristics and requirements of the pilot assembly system and corresponding facility. In particular, the required key process data in terms of Cycle Time (CT), Uptime (UT), First Pass Yield (FPY) and Energy Efficiency Improvement Factors $f_{EEIF\,j}$ of each technology j with respect to the Direct Energy Consumption are verified and validated in cooperation with experts of the Beijing Plant, as Table 1 illustrates.

Table 1. Influence of Smart Automation technologies on process data

No.	Abb.	Technology	CT [Sec.]	UT [Sec.]	FPY [%]	$\mathbf{f_{EEIF}}_j$ [%]
T1	PBL	Pick-by-Light	-0.02	-0.03	-0.33	-0.10
T2	HMI	Human Machine Interface	-0.08	-0.11	-0.05	-0.05
T3	QR	QR-Code	-0.50	-0.09	-0.05	-0.10
T4	INS	Intelligent Screwdriver	0.00	0.00	-0.33	-0.05
T5	WN	Wireless Nut Runner	-0.07	-0.03	-0.33	-0.05
T6	AGV	Automatic Guided Vehicle	0.00	-0.10	-0.05	0.00
T7	ATA	Automatic Torque Adjustment	-0.04	-0.05	-0.05	-0.02
T8	CPM	RFID-based C-Parts Management	0.00	0.00	-0.05	-0.05
T9	WCR	Workpiece Carrier with RFID Tags	-0.06	-0.08	0.00	-0.05
T10	DSFM	Digital Shopfloor Management	-0.05	-0.05	-0.10	-0.15
T11	MES	Manufacturing Execution System	-0.04	-0.06	0.00	-0.10
T12	SG	Smart Gloves	-0.05	0.00	-0.10	-0.05

For the purpose of adapting the KPI structure, the items taken into account for the calculation of the Indirect Energy Consumption were reviewed with employees from the energy management and the digitalization departments of the Beijing Plant. Moreover, the Average Consumption Rate$_i$ (ACON$_i$) of each item i, the corresponding Recycling Factor$_i$ (RF$_i$), as well as the associated amount of emitted CO2 in terms of the appropriate CO2-Equivalent-Factor$_i$ (CO2EQF$_i$) were identified. With regard to the factors, metrics from databases of various lifecycle assessment software, namely GaBi and SimaPro, as well as the database 'Prozessorientierte Basisdaten fuer Umweltmanagement' (ProBas) maintained by the federal environmental agency were considered and aligned. Table 2 shows the results of the adapted list of items with respect to the pilot assembly line of the Beijing Plant over the observed time period of eight hours, which corresponds to the duration of one shift. However, as stated by a representative of the facility, the planned operating time per week is 144 hours in total. Therefore, the values for the simulation process are scaled accordingly.

Table 2. Items for the calculation of the CO2-Equivalent of the pilot system of Beijing Plant.

i	Item	Group	ACONi	RFi	CO2EQFi
1	Material Scrap	Material	Cast Iron: 3.00 kg per part	0.00	1.51
2	Tool Scrap	Material	Stainless Steel: 0.02 kg per shift	0.00	6.15
3	Wood	Packaging	16.03 kg per shift	0.00	2.42
4	Carton	Packaging	0.53 kg per shift	0.00	2.12
5	Synthetics	Packaging	Plastics: 35.77 bags per shift Desiccant: 3.72 units per shift	0.00 0.00	1.58* 5.80*
6	Water	Liquid	216.25 liters per shift	0.00	0.03**
7	Lubricants	Liquid	Not applicable	-	-
8	Chemicals	Liquid	Not applicable	-	-

*Factor not per kg, but per unit; **Factor not per kg, but per liter

4.3. Adjustments to the simulation model

The simulation model for the Beijing Plant is implemented in the AnyLogic® simulation environment. The implementation process of the different technologies is realized by using SD modeling. The assembly system, which consists of multiple workstations, is conceptualized with the methods of DES and ABS in order to realize the modular modeling approach. However, the processes at the operational level within the individual workstations are represented by the concept of DES. The performance of the system with reference to the implementation progress and the corresponding effect of the different technologies is measured by a total of five key figures, which are visualized with the help of several line diagrams (see Appendix 1).

4.4. Derivation and evaluation of implementation strategies

According to the management board of the Beijing Plant, all metrics included in the objective function (see Appendix 2) are of equal priority for further investigations. The total investment and the overall implementation duration are the binding restrictions. The technologies Intelligent Screwdriver (INS) and Automatic Torque Adjustment (ATA) were not considered when deriving an optimal implementation sequence, as they are already fully implemented in the pilot assembly system at the Beijing Plant.

The sequence of the remaining ten technologies to be implemented at the Beijing Plant was optimized by using an optimization tool based on Visual Basic for Application©. Table 3 shows the best five sequences of the scenario with sufficient investment budget as well as unlimited implementation duration in order to represent the overall impact on the key figures after the implementation of all technologies. For reference purposes, an initial sequence was also defined.

Table 3. Ranking of optimal implementation sequences of Smart Automation technologies

i	PBL	HMI	QR	WN	AGV	CPM	WCR	DSFM	MES	SG
1	1	5	3	2	8	10	4	7	6	9
2	1	5	3	2	8	9	4	7	6	10
3	2	5	3	1	8	10	4	7	6	9
4	2	5	3	1	8	9	4	7	6	10
5	1	5	4	2	8	10	3	7	6	9
…	…	…	…	…	…	…	…	…	…	…
Initial Sequence	10	5	7	6	1	2	4	8	3	9

As Figure 3 shows, an overview of the final simulation results of the top ranked implementation sequence compared to the initial sequence is represented. Although in the end both strategies applied to the pilot assembly system produce almost identical results, the benefits of a coordinated implementation strategy of Smart Automation technologies are apparent in achieving these results earlier. Deviations in terms of the KPIs Quality, Delivery and Environment are due to the consideration of the produced output and the associated fluctuations in the simulation.

In particular, the curves of the energy consumption of the initial implementation strategy show a constant, even slightly rising trend at the beginning, indicating an increase in emitted emissions. However, this course is due to an improvement in Uptime and the resulting increase in the ratio of production time and idle time. With respect to the optimal implementation strategy, this behavior is counteracted by an early occurrence of efficiency improvements in terms of both Direct Energy Consumption and Indirect Energy consumption. Additionally, the change in Indirect Energy Consumption is almost congruent with the trend in Total Energy Consumption due to its relatively larger share of the impact.

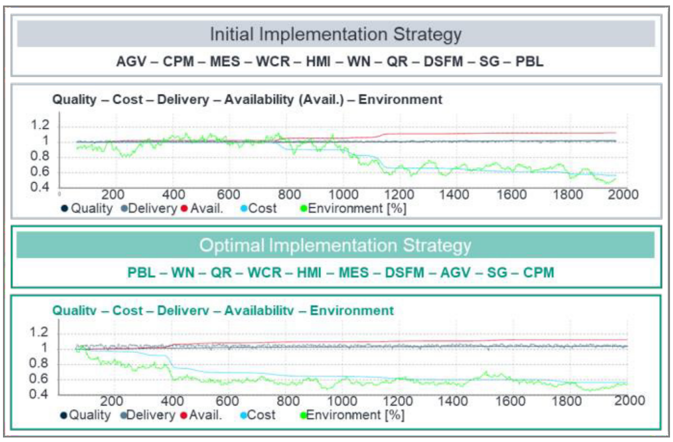

Fig. 3. The improvements by initial vs. optimal implementation strategy

The result of the sensitivity analysis for the optimal implementation strategy uses the methodology of Monte Carlo simulation. The influence of location factors on the technology implementation, the influence of technologies on the process data, as well as the interdependencies between the different technologies were investigated with 200 iterations of factor variations. The sensitivity analysis reveals that the values deviate from the previous performance, but are still within a reasonable range without significant outliers. The mean value of the observed changes of the final KPIs is 0.330, which is slightly lower than the value of 0.332 obtained from the previous simulation run. However, the sensitivity analysis still shows that the values are relatively stable with variations in expert input as more iterations are performed. Consequently, the implementation strategy identified as optimal within this approach can be recommended for the pilot assembly system of the Beijing Plant.

5. Conclusion

The proposed approach for the development of a sustainability-oriented implementation strategy of Smart Automation technologies in assembly systems derives an optimized outcome based on a set of key figures and enabled through hybrid modeling and simulation, taking into account the technology-specific characteristics, the local conditions, the company-specific initial situation as well as the interdependencies between these disciplines. On the basis of a scientifical and rational analysis, the application of the simulation model enables industrial companies to effectively determine a tailored implementation sequence of disruptive technologies with respect to regionalized and company-specific conditions. The specified and leading research questions and requirements have been comprehensively addressed.

The data quality influence to a certain degree the performance of hybrid modeling and simulation. Due to the difficulty of obtaining accurate data from partnering plants for each technology, the factors were determined by contacting experts from leading manufacturers of reference systems and referring to use cases. In future, the investigations could be initiated on a cross-manufacturer basis in order to determine average values. As another future work, all three dimensions of sustainability need to be considered such as define a metric for social sustainability in addition to the classic KPIs, which could contribute to the human-centric working systems.

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