D1.2

ANALYSIS OF BUSINESS VALUE CREATION ENABLED BY 5G FOR MANUFACTURING INDUSTRIES

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D1.2 - Analysis of business value creation enabled by 5G for manufacturing industries

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Short abstract:	The report covers an assessment framework created to quantify the business value of 5G implementation for industrial actors. The development of this model is described, as well as its implementation into a model. Finally, the model is applied to an AGV use case to show its usability.

Keywords:	Economic analysis framework; production companies; economic evaluation; technological analysis

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Disclaimer

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Executive summary

Within the activities of 5G-SMART, an assessment framework was created to quantify the business value of 5G implementation for industrial actors.

This report presents a 4-step model supporting the economic evaluation of 5G implementation for applications in production. Step 1 (Requirement Check) includes use case selection as well as the network requirement selection from the end-user point of view. In step 2 (Goal Definition), technical and economic goals are determined. Seven technical goals and two economic goals can be selected. It is possible to select more than one goal at a time. Selected goals decide on which data is required to evaluate the process. In step 3 (Data Acquisition) model user has to provide the data of the use case to be analyzed. Technical and economic potential of 5G for user's application is given in step 4 (Process Evaluation). The framework is implemented in an excel tool and applied on an Automated Guided Vehicle (AGV) use case. It is emphasized that this framework focuses on the improvements coming from the implementation of 5G without any claim to completeness. All selected technical and economic data is 5G-related. This means that the framework does not provide a full techno-economic analysis of a typical production application. Presented changes through 5G are based on literature only.

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1 Introduction

1.1 Motivation

Between 2021 and 2025, Industry 4.0 technologies are expected to increase gross margins of the production industry by up to 13 % [Abi19]. An increase in output quality and a decrease in both wasteful output and downtime will increase productivity [ALB+18; TMK19]. Essential enablers for this improvement are applications such as closed-loop control, predictive maintenance, digital twins, augmented reality, and automated guided vehicles. For all these applications, suitable industrial communication systems play a decisive role. Communication systems have to be reliable, scalable, decentralized, and transmit data in near real-time [Abi19]. The 5G mobile communication standard appears to be an effective way to achieve a communication system for networked, adaptive production. As wireless communication technology, 5G technology can substantially reduce installation and maintenance costs while easily connecting mobile or inaccessible devices and simplifying line layout. 5G technology is therefore expected to increase worldwide production industry gross domestic product (GDP) by up to $740 billion until 2030 [Adi19].

These 5G-enabled opportunities are reflected in a survey conducted among 505 production companies in Germany in 2019. 84 % endorse the predictions on massive benefits from 5G for productivity, 93 % expect a supporting role to Industry 4.0, and 70 % see 5G technology as an essential future technology. However, 55 % of the participating companies state that 5G technology deployment is currently not a subject of matter for them; more than half of those cite a lack of knowledge on benefits as a reason. One in three companies reports not having budgeted any 5G investment yet. [Bit19]

From these findings, it becomes clear that uncertainty is inhibiting investment so far. The main reason for this is that an economic evaluation of 5G-enabled benefits for specific production use cases from an end-user perspective is not widely established yet. The end-user, in this case, is the person in the production company being responsible for implementing 5G for, e.g., process control, automated guided vehicles (AGVs), or augmented reality. The improvement potential for production processes needs to be quantified. Thus, the monetary benefits from these potentials provide decision-makers with a sound base for proceeding with the investment. Therefore, in 5G-SMART an assessment framework was created to quantify the business value of 5G implementation for industrial actors.

1.2 Objective

The objective of this document is to describe the assessment framework that has been developed to quantify the business value of 5G for industry applications. Relevant input and output parameters are explained, and it is shown in what way the framework provides decision support to manufacturing owners, production planners, and technology developers. The framework focuses on brownfield investment, which means that it can only be applied to applications that a company already operates and therefore has access to data to. By setting relevant goals and Key Performance Indicator (KPIs) and entering relevant data, the model user can determine both the technical and economic potential of 5G. The framework is designed to be applicable for any company size with relation to production. No assumptions are made regarding revenue, number of employees, or gross profit of company. By requesting all relevant data from the model user, the model also allows guidance for small-sized companies to assess the evaluation of their potential of implementing 5G. It is important to note that the model can only be used for assessing one application at a time although it is possible to include up to three additional specific production technologies that are enabled by 5G.

1.3 Relation to other documents in 5G-SMART

This deliverable takes input from the discussions on use cases, requirements and KPIs described in Deliverable D1.1 [5GS20-D110], as well as architecture structures discussed in Deliverable D5.2 [5GS20-D520]. It has a close relation to the upcoming deliverable D1.3, which, in contrast to this deliverable, dives deeper into a business analysis of different deployment options.

1.4 Structure of the document

This deliverable is divided into seven chapters. After introducing and defining the most important terms for the further course of this deliverable (chapter 2), chapter 3 describes in detail how the model was developed. In chapter 4, the effects of 5G on production are derived according to the framework. In chapter 5, the implementation of the framework into an Excel tool is described. Chapter 6 applies the framework exemplary to an AGV use case. Finally, chapter 7 summarizes the results and gives an outlook for future research to improve the framework and the economic evaluation of the 5G-enabled potential for end users in production.

2 Definition of terms & frame of references

2.1 Definition of terms

2.1.1 Technical evaluation

Justification of investments in new technologies requires convincing arguments as well as a defined goal. [SSW12] analyzed the evolution of performance measures in the manufacturing industry. Until 1990, companies focused on pursuing a single goal: decreasing cost, increasing productivity, or enhancing quality. Since the 90s, multi-dimensional performance measures evolved to cope with the increasing complexity of manufacturing systems. Overall goals of Industry 4.0 are increasing operational productivity and efficiency through automation and connection of the physical and virtual world [AC19]. Further goals are improving flexibility, versatility, and usability of smart factories [5GACIA1]. Costs and revenues are important measures to determine the profitability of an application. In this framework, they are not part of technical but economic evaluation (see definition in chapter 2.1.3).

Each goal is assessed on basis of individual technical key performance indicators (KPI), which are defined in chapter 2.1.2.

2.1.2 Key performance indicators

Key performance indicators (KPIs) are a widely used instrument to detect changes in production system performance [SEL+17; HWA+17]. KPIs are critical for assessing the manufacturing operation management and continuous improvement. In modern manufacturing systems, KPIs are defined as a set of metrics to reflect operation performance, such as efficiency, throughput, availability, which are regarded from productivity, quality and maintenance perspectives [KAN+16; AFM+18]. They quantify the level of achieving a critical objective [ISO22400], and are a widespread method for communicating goals throughout the organization, which is the production company in the course of this report [PH14; FRA+07]. KPIs are used on all levels, be it strategic, tactical or operational [TGJ+16], and may even be used for predictive production control [MS17]. For automation systems and integration, ISO22400 specifies several criteria for a KPI to be a “good KPI”, such as validity, quantifiability, and accuracy [ISO14a; ISO14b]. ISO22400 is therefore the basis for the chosen KPI set presented in this report.

2.1.3 Economic evaluation

Traditional investment decisions are often evaluated based on discounted cash flows [DA92]. Discounted cash flows determine future cash flows generated by technology corrected for their risk [VV07]. Economic key figures based on this principle are net present value (NPV), return on investment (RoI), and internal rate of return (IRR) [DA92]. NPV method is based on the time value of money where the future value of money equals the present value of money invested at a specific interest rate [SD97]. NPV is calculated by Equation (1) [SSW12]:

$$NPV = \sum_{t=0}^{T} \frac{CF_t}{(1+i)^t} \quad (1)$$

with:

- NPV = today's value
- CF_t = cash flow in period t
- i = applied interest rate
- T = time

IRR determines the discount rate, leading to a net present value of future cash flows equal to 0 [SD97]. IRR is applicable when investments with flexible cash flows are compared. In this framework, it is assumed that constant cash flows are generated over the application's lifetime, so IRR is not considered an economic key figure. To calculate the cash flows of investments, capital expenditure (CAPEX) and operational expenditure (OPEX) are common measures to determine the application costs. CAPEX determines initial investment in a technology, product, or service, including all acquisition costs for new equipment [BKK+18]. OPEX determines cash flows over an asset's lifetime, including maintenance, operation, or power consumption costs [BKK+18]. Cash flow (CF) in period t = 0 is calculated by Equation (2):

$$CF_{t=0} = -CAPEX \quad (2)$$

Equation (3) shows the calculation of CF in periods t > 0.

$$CF_{t>0} = Revenues_t - OPEX_t \quad (3)$$

RoI, expressed in percentage, includes initial investment, and estimations of net annual revenues and annual project cost [SD97]. RoI, in addition, determines operational cost savings that can be used to either improve gross profit margin, expand working capital, or enhance production capacity [BOS20+]. RoI is calculated by Equation (4):

$$RoI = \frac{Profit}{Total\ capital} = \frac{NPV_{Revenues} - NPV_{Cost}}{CAPEX} \quad (4)$$

2.2 Application area of framework

In the 5G ecosystem of a manufacturing company, several stakeholders are interrelated. D5.2 [5GS20-D520] of 5G-SMART defines mobile network operator (MNO), industrial party and 3rd party. The roles of the stakeholders depend on the operation model. This means, for example, that the industrial party can be both provider and consumer of the non-public 5G network. Nevertheless, the "original" value creation at the industrial party is always the improvement of the production process itself. The manufacturer creates value and revenues by improving its production, especially through digitalization. This created revenue defines at the same time the maximum price the manufacturer is willing to pay for the 5G network and additional cost towards related devices, automation, application, 5G network competence development. In order to be clear within this deliverable (D1.2), Figure 2.1 shows the focus of the report at hand.

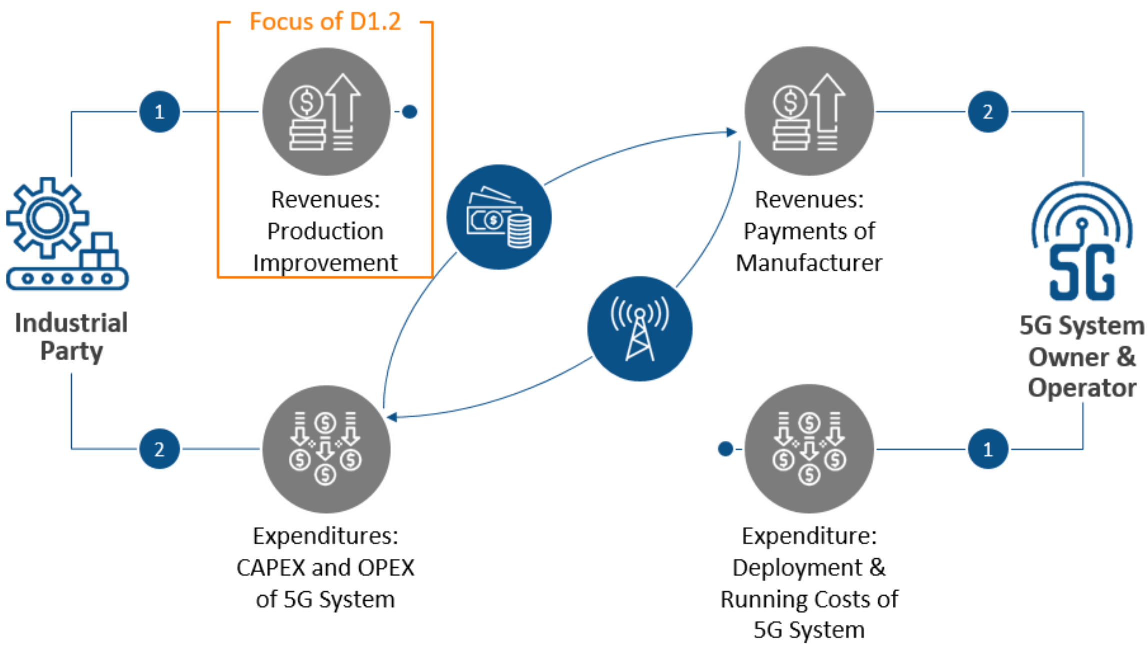

Figure 2.1: Value creation within the manufacturing ecosystem enabled by 5G implementation

D1.2 focuses on the described **revenues manufacturers can create by implementing 5G technology in production and thus defines the maximum price production companies are willing to pay for 5G technology**. Due to this focus, the results are independent from the operation model. Thus, operation models are not further differentiated in the further course of this report but are instead discussed in 5G-SMART's deliverable D1.3 due in July 2021.

3 Development of model to evaluate 5G technology in manufacturing companies

This chapter describes how the framework for the quantification of 5G-business value for industrial actors was developed. Chapter 3.1 summarizes purpose as well as main requirements of the evaluation framework. Chapter 3.2 describes the overall architecture of the evaluation model. Chapter 3.3, 3.4 and 3.5 describe the contents of the four modules of the evaluation model.

3.1 Purpose, requirements and limitations of evaluation model

3.1.1 Purpose and methodology of the evaluation model

Motivation for this framework is providing decision support to manufacturing owners, production planners, and technology developers. In this framework, the **brownfield investment strategy** is focused, which means that a company already operates the production process and considers the implementation of 5G technology to improve the process.

The framework aims to empower production planners to evaluate the potential of 5G technology on their own. Therefore, the production planner, or rather a model user, is asked to provide data regarding the status quo of his or her application. Status quo refers to the application using wired communication. The status quo is analyzed both from technical and economic perspectives. In the next step, expected changes through implementing 5G use cases and their economic effects are analyzed and applied to the status quo. Finally, the user gets results on how 5G might impact his or her production application.

The framework is designed to be applicable for any company size with relation to production. In contrast to Ericsson's use case analysis [EHL20], no assumptions are made regarding revenue, the number of employees, or the company's gross profit. Instead, this framework aims to enquire about all relevant numbers from the user. In this way, even small-sized companies can benefit from this framework and evaluate their potential benefit of implementing 5G. Note that the model can only be applied to one application at a time.

3.1.2 Capabilities of evaluation model

When developing the model, certain capabilities were defined by both literature and through interviews with potential model users [KS20]. These are summarized in the following.

- ***Target group: manufacturing use case owners in the planning phase***
  The model addresses responsibles and owners of manufacturing use cases which are in the 5G planning phase (no 5G implemented yet).
- ***Evaluation object: production use case***
  The object is a single use case in production
- ***Evaluation approach: data-based quantification***
  The use case should be evaluated based on product and process data from the currently implemented use case.
- ***Evaluation dimension: technical and economic evaluation***
  The model should calculate both the technical and economic benefits of the 5G implementation as defined in *chapter 2.1.*
- **Decision support: user-specific individualization**
  The model should allow users to choose the goals individually based on his or her preferences.

3.1.3 Limitations of evaluation model

It is emphasized that this framework focuses on the improvements coming from the implementation of 5G without any claim to completeness. All selected technical and economic data is 5G-related. This means that the framework does not provide a full techno-economic analysis of a typical production application. Presented changes through 5G are based on literature only.

3.2 Evaluation model architecture

The evaluation model includes four steps. *Figure 3.1* summarizes the four steps.

Figure 3.1: Structure of the developed evaluation model within A1.2 of 5G-SMART

Step 1 (Requirement Check) includes use case selection and the network requirement selection from the end-user point of view. In step 2 (Goal Definition), technical and economic goals are determined. Seven technical goals and two economic goals can be selected. It is possible to select more than one goal at a time. Selected goals decide on which data is required to evaluate the process. In step 3 (Data Acquisition), the model user has to provide the data of the use case to be analyzed. Finally, the technical and economic potential of 5G for the user's process is given in step 4.

3.3 Use Case Requirement Check

The first step of the model is the requirement check. This helps the user to figure out at an early evaluation stage whether the 5G capabilities really support the use case. Therefore, the model includes several use cases. The model user can select one of the following use cases, being interrelated to the technical goals.

- **Control-to-control**
  Control-to-control (C2C) communication is between industrial controllers (e.g. programmable logic controllers or motion controllers).
- **Mobile control panels (with safety function)**
  Mobile control panels are crucial for the interaction between workers and production equipment (e.g., for configuring, monitoring, or debugging machines).
- **Motion control**
  A motion control system is responsible for controlling moving and/or rotating parts of machines in a clearly defined way.
- **Factory automation – control**
  Sensor-captured data is transferred to a controller which then decides whether and how to operate actuators.
- **Factory automation – monitoring**
  Sensor-captured data is transmitted to displays for observation and/or database for logging and trend monitoring.

Step 1 also includes the definition of network requirements for the application. The user is asked to set the values for the required latency, reliability, availability, data rate, connection density, localization precision, communication range, and mobility of the application. The morphology in *Figure 3.2* was developed to determine which communication network is suitable for each requirement. On basis of the morphology, ten different communication technologies (CT) are compared, namely LoRaWAN, 6LoWPAN, Bluetooth, WISA, ISA 100.11, WirelessHART, ZigBee, Wi-Fi, 4G, and 5G. Based on the inserted network requirements, a recommendation is given which communication technologies meet the requirements. The ten CTs are classified in Figure 3.3.

Latency (ms)	>100	100-50	50-20	20-10	10-1	<1	
Reliability (%)	<90	90-99	99-99.9	99.9-99.99	99.99-99.999	99.999-99.9999	>99.9999
Availability (%)	<90	90-99	99-99.9	99.9-99.99	99.99-99.999	99.999-99.9999	>99.9999
User Data Rate (Mbps)	<5	5-100	100-1000	1000-5000	5000-10000	>10000	
Connection Density (Dev./m²)	<0.01	0.01-0.1	0.1-1	1-10	10-20	>20	
Localization Precision (m)	N/A	>10	10-1	1-0.1	0.1-0.01	<0.01	
Communication Range (m)	<1	1-5	5-10	10-50	50-100	100-1000	>1000
Mobility (km/h)	N/A	<5	5-50	50-100	100-500		

Figure 3.2: Morphological box to pre-evaluate the use case

Below the parameters of the morphological box are listed together with their definitions as provided in 5G-SMART's deliverable D1.1 [5GS20-D110].

Latency - ms
(End-to-end) Latency is the time that it takes to transfer application data of a given size from a source to a destination, from the moment it is transmitted by the source to the moment it is successfully received at the destination (one-way latency).

Reliability - %
The communication service reliability relates to the ability to continuously operate as required by the application, without failure, for a given time interval and under given conditions (e.g. mode of operation, stress levels, and environment). It can be quantified using metrics such as mean time between failures (MTBF) or the probability of no failure within a specified period of time. MTBF is the mean value of how long the communication service is available before it becomes unavailable.

Availability - %
The communication service availability relates to the ability to allow correct operation of the application. It is defined as the "percentage value of the amount of time the end-to-end communication service is delivered according to an agreed QoS, divided by the amount of time the system is expected to deliver the end-to-end service according to the specification in a specific area". The service is unavailable if the messages received at the target are impaired and/or untimely (e.g. latency > stipulated maximum), resulting in survival time being exceeded.

User Data Rate - Mbps
The user data rate is defined as the value of the number of bits transmitted or received over time, typically expressed in Mbit/s, which is expected to be measured at the CSI. This definition excludes scenarios for broadcast-like services, where the given value is the maximum that is needed.

Connection Density - Dev./m²

The required connection density is typically measured in devices/m². It is defined as the number of devices performing on a certain area unit. The characteristic can be specified regarding the maximum, minimum or average value. It can also be defined per volume, depending on the given application and use case. Because of the CT's variety in this characteristic, for certain use cases special requirements are given. Hence, only some of the possible CTs are appropriate and cost efficient.

Localization Precision - m [MTA+18]

Positioning is vital to ensure accurate tracking of devices, guarantee safety standards, and enable factory and process automation applications. For some use cases, accuracy within a few centimeters (cm) is required, whereas other applications need a positioning of some meters (m). For most control and automation systems, positioning precision in sub-meter accuracy is efficient. The related localization/positioning error, also typically given in meter, is defined as "the value of the difference between the estimated position of an object and its real location, according to a reference coordinate system".

Communication Range - m

The communication range in meter indicates the possible range a communication technology can enable the transfer of data and information between sender and receiver. Different applications require ranges from 'less than 1 m' while others need ranges up to 'more than 1000m'.

Mobility – km/h

Industrial use cases with requirements regarding communication technology can be ranked regarding mobility. Some applications are characterized by higher mobility, such as transportation or logistics, whereas others are more local and with low mobility. Configurations range from 'less than 5km/h' to '500km/h'.

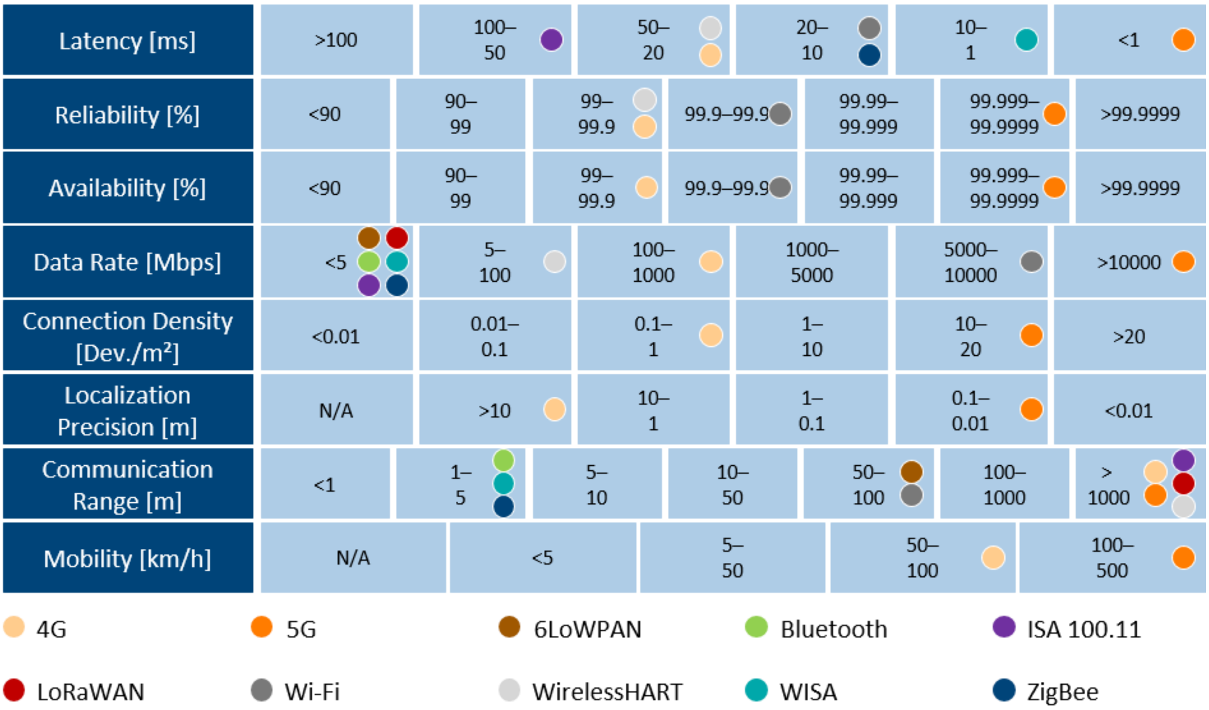

Figure 3.3: Classification of CTs in the morphology (maximum values)

3.4 Goal Definition

This section comprises technical and economic goal criteria. Goal criteria are selected based on literature and expert knowledge. Setting goals is essential to align a company's focus. A company can only manage what it can measure, and it can only improve upon something that it appropriately manages. Regarding the implementation of 5G, setting goals helps a company figure out what it expects from 5G. In this case, the framework can support a company in deciding whether 5G technology is an appropriate instrument to improve upon its goals.

3.4.1 Technical Goals and Manufacturing-KPIs

In order to determine technical goals, a literature review of evaluating manufacturing technologies has been performed (Figure 3.4).

Goal	[DEMM92]	[ABDU94]	[UPTO95]	[MILT05]	[CHAN09]	[QUEZ09]	[KOHO10]	[ANVA11]	[SCHU12]	[SCHU12]	[SCHU12]	[SCHU12]	[SCHU12]	[IEC13]	[KARI13]	[GUST13]	[ISO14a]	[ISO14a]	[ISO14a]	[ISO14a]	[GRIE17]	[AKER18]	[BARA19]	Σ SUM	Report
Availability																x								1	
Convertibility																						x		1	
Cost				x		x	x		x	x		x	x				x							8	
Customization																						x		1	
Demand Increase											x													1	
Dependability										x														1	
Design	x																							1	
Effectiveness															x						x			2	
Efficiency		x													x									2	
Equipment	x																		x					2	
Flexibility	**x**	**x**	**x**	**x**			**x**		**x**	**x**		**x**	**x**				**x**							**10**	**x**
Innovativeness				x																				1	
Integration	x																							1	
Internal Relations	x																							1	
Inventory														x				x						2	
Logistics												x												1	
Maintenance	x	x												x		x		x						5	
Market Position	x																							1	
Material	x																		x					2	
Mission	x																							1	
Mobility			**x**																			**x**	**x**	**3**	**x**
Modularity																						x		1	
Organization	x																							1	
Performance				x											x									2	
Personnel	x																		x					2	
Price		x									x													1	
Process																			x	x			x	3	
Product	x																			x				2	
Product Range											x													1	
Produceability	x																							1	
Production														x				x		x				3	
Productivity												**x**			**x**	**x**								**3**	**x**
Public Relations	x																							1	
Quality		**x**		**x**			**x**		**x**	**x**	**x**	**x**	**x**	**x**	**x**		**x**	**x**						**12**	**x**
Reliability		x		x			x				x					x								5	
Responsiveness		x																						1	
Safety					**x**			**x**								**x**								**3**	**x**
Scalability																						x		1	
Speed										x	x													2	
Sustainability												**x**	**x**				**x**							**3**	**x**
Technology	x																							1	
Time							x		x			x					x							4	
Utilization						**x**									**x**						**x**			**3**	**x**
Value																							x	1	

Figure 3.4: Literature review of production goals

As Figure 3.4 shows, the most frequently used technical goals are quality (12 citations), flexibility (10 citations), cost (8 citations), maintenance (5 citations), reliability (5 citations), and time (4 citations). Further frequently used goals include mobility (3 citations), production (3 citations), productivity (3 citations), safety (3 citations), sustainability (3 citations), and utilization (3 citations). Based on both literature and workshops that were held with industry partners, seven top-level objectives are selected to evaluate the technical potential of 5G, as Figure 3.5 shows.

Figure 3.5: Technical goal criteria for the use case analysis

The goals are defined in the following:

- **Flexibility** describes the ability to process many different parts within the manufacturing system with minimum engineering effort and changeover time [Lap14].
- **Mobility** describes the ability of moving objects on the factory shopfloor [ISO14a, Lap14].
- **Productivity** measures the output per unit of input over a specific period of time and therefore denotes the production efficiency [Lap14].
- **Quality** rates the degree to which the output of the production process meets the requirements [ISO14a].
- **Safety** is the ability of a system to protect itself and the operator from harm or accidents [ISO14b].
- **Sustainability** describes the level to which the creation of manufactured products is fulfilled by processes that are nonpolluting, conserve energy and natural resources [Lap14].
- **Utilization** is the ratio of actual used machining time compared to the theoretically available time [Lap14].

As chapter 2.1.2 describes, many KPIs are existing in literature which are partially redundant or difficult to measure. To have a meaningful set of KPIs that reflects the goals of 5G technology implementation, but is still manageable, we derived a compact, but complete set of KPIs. In order to achieve this, we compared KPIs on the level of their formulas and elements to make sure, that important elements are covered, but not repeating. Figure 3.6 exemplary shows the KPI derivation for the goal *Quality*.

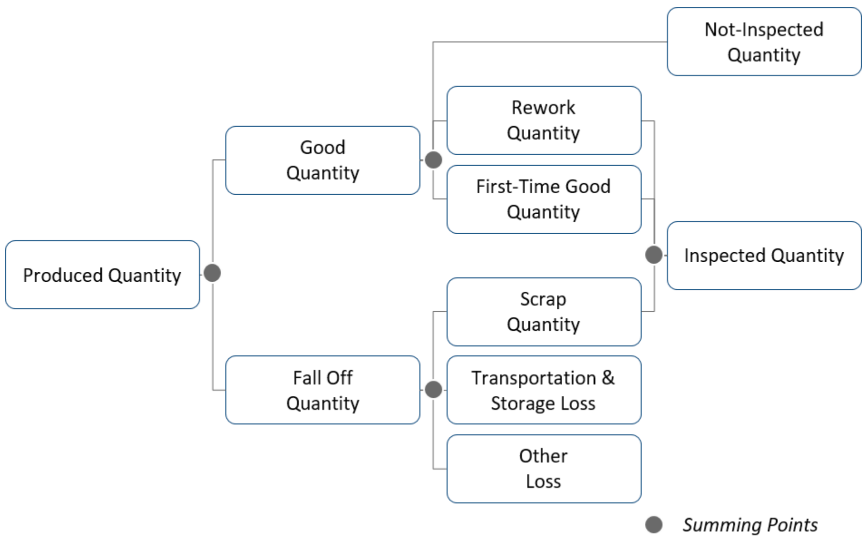

Figure 3.6: Relation of KPI-formula-elements of the goal “quality”.

Quality is often measured based on the produced quantity. Figure 3.6 shows the elements that are related to produced quantity. Based on our literature research, twenty different KPIs were found which are only using the shown ten elements.

We first operationalized all KPIs. Second, we eliminated those, whose elements are not clearly defined (e.g. other loss) or difficult to measure. Third, based on simulations with data sets, we eliminated redundant KPIs. Thus, four KPIs were chosen to express *Quality*:

- *First Pass Yield (FPY)* expresses the amount of goods meeting quality requirements in the first production cycle.
- *Quality Ratio (QR)* calculates total amount of goods meeting quality requirements compared to total amount of produced goods.
- *Rework Ratio (RR)* expresses the ratio of parts needing rework compared to total amount of produced goods.
- *Scrap Ratio (SR)* expresses the ratio of destroyed parts compared to total amount of produced goods.

These KPIs are assigned to their optimum max or min. *Max* means, that the KPI has to be increased to improve the goal (e.g. higher quality ratio = higher quality). *Min* on the other hand means, that a decreased KPI improves the goal (e.g. lower scrap ratio = higher quality). This trend is relevant, once the change of KPIs after 5G technology implementation is traced back to the goal. As all goals have a positive trend, the max-KPIs are added with a positive sign, the min-KPIs with a negative sign. For the goal *Quality*, this relation is expressed in Equation (5).

$$\Delta Quality = \frac{\Delta FPY + \Delta QR - \Delta RR - \Delta SR}{4} \quad (5)$$

Table 3.1 summarizes the developed KPI-set. Thereby, KPIs are assigned to their respective goal, operationalized with a formula and assigned to an optimum.

Goal	KPI	Formula & Elements	Optimum
Flexibility	Machine Flexibility (MF)	$\frac{Potential\ Product\ Variants}{Machines}$	Max
	Setup Ratio (SUR)	$\frac{Actual\ Unit\ Setup\ Time}{Actual\ Unit\ Processing\ Time}$	Min
Mobility	Material Handling Mobility (MHM)	$\frac{Paths\ Supported\ By\ System}{Total\ Number\ of\ Paths}$	Max
	On-Time Delivery (OTD)	$\frac{On-Time\ Customer\ Orders}{Total\ Customer\ Orders}$	Max
	Space Productivity (SP)	$\frac{Total\ Plant\ A. - Rework\ A. - Storage\ A. - Manufacturing\ A.}{Total\ Plant\ A.}$	Max
Productivity	Effectiveness (E)	$\frac{Planned\ Runtime\ \cdot Produced\ Quantity}{Actual\ Application\ Production\ Time}$	Max
	Throughput Ratio (TR)	$\frac{Produced\ Quantity}{Actual\ Application\ Execution\ Time}$	Max
	Worker Efficiency (WE)	$\frac{Actual\ Personnel\ Work\ Time}{Actual\ Personnel\ Attendance\ Time}$	Max

Quality	First Pass Yield (FPY)	$\frac{First\ Time\ Good\ Quantity}{Inspected\ Quantity}$	Max
	Quality Ratio (QR)	$\frac{Good\ Quantity}{Produced\ Quantity}$	Max
	Rework Ratio (RR)	$\frac{Rework\ Quantity}{Produced\ Quantity}$	Min
	Scrap Ratio (SR)	$\frac{Scrap\ Quantity}{Produced\ Quantity}$	Min
Safety	Accident Ratio (ACCR)	$\frac{Number\ of\ Accidents}{Actual\ Personnel\ Attendance\ Time}$	Min
	Mean Operating Time between Failures (MTBF)	$\frac{Time\ between\ Failures}{Number\ of\ Failure\ Events + 1}$	Max
	Mean Time to Repair (MTTR)	$\frac{Time\ to\ Repair}{Number\ of\ Failure\ Events + 1}$	Min
Sustainability	Carbon Weight (CW)	$Total\ Energy\ Consumption\ \cdot Convergence_{(kWh \to CO_2)}$	Min
	Compressed Air Consumption Ratio (ACR)	$\frac{Compressed\ Air\ Consumption}{Produced\ Quantity}$	Min
	Electric Power Consumption Ratio (ECR)	$\frac{Electric\ Power\ Consumption}{Produced\ Quantity}$	Min
	Gas Consumption Ratio (GCR)	$\frac{Gas\ Consumption}{Produced\ Quantity}$	Min
	Water Consumption Ratio (WCR)	$\frac{Water\ Consumption}{Produced\ Quantity}$	Min
Utilization	Allocation Efficiency (AE)	$\frac{Actual\ Application\ Busy\ Time}{Planned\ Application\ Busy\ Time}$	Max
	Availability (A)	$\frac{Actual\ Application\ Production\ Time}{Planned\ Application\ Busy\ Time}$	Max
	Technical Efficiency (TE)	$\frac{Actual\ Application\ Production\ Time}{Act.Appl.Production\ Time + Act.Appl.Delay\ Time}$	Max
	Utilization Efficiency (UE)	$\frac{Actual\ Application\ Production\ Time}{Actual\ Application\ Busy\ Time}$	Max

Table 3.1 KPI-set to quantify production process performance by implementing 5G technology

3.4.2 Economic Goals

Net present value and **return on investment** are selected as economic indicators in this framework. The economic evaluation is complemented by technical evaluation measures to compensate for disadvantages of traditional economic key figures such as neglection of intangible benefits (Equations are given in *chapter 2.1.3).*

3.5 Data Acquisition

To realize the requirements for the data-based evaluation approach (see chapter 0), data to be acquired has to be defined. To clarify the definition of the word 'data', it is defined as follows:

- Data can be determined by a numeric value larger than or equal to zero
- Unit of data is given and unique
- Data is not redundant
- Data has a direct or indirect effect on KPIs. The effect is direct when data represents a KPI element (e.g. produced quantity). The effect is indirect when data impacts a KPI element (e.g. time for repair, which impacts the KPI element rework quantity).

Five data categories are distinguished, namely:

- Product data (Chapter 0)
- Process data (Chapter3.5.2)
- Failure data (Chapter 3.5.3)
- Facility data (Chapter 3.5.4)

Data is collected to gain production use case-specific information. Each category is further separated into technical data and economic data to evaluate both the technical and economic potential of 5G.

Chapter 0 to Chapter 3.5.4 summarize and explain the data which directly has to be acquired by the user of the model. The mathematical relations and equations between this data and the goals and KPIs are given in the appendix (see A2: Mathematical equations).

3.5.1 Product Data

Product data describe the quantity, quality and type of products that are produced by the application. Table 3.2 summarizes the necessary technical and economic product data to be acquired (sorted in alphabetic order).

Necessary Product Data	Explanation	Unit
Additional expected profit by individualization	In the event of individualized product variants, how much is the expected additional net profit for each sold product?	Euro/part
Average material cost for rework	Average cost spent on material to perform (manual or automatic) rework of a single part	Euro/part
Disposal cost per part	Additional cost spent on disposal in the event of scrap	Euro/part
First time good quantity	Number of parts that pass quality control in the first instance	Parts/day
Hourly wage of rework staff	Hourly wage of a worker, technician, or engineer who is responsible for manual rework	Euro/hour
Inspected quantity	Number of parts that undergo quality control	Parts/day
Material cost per part	Average material cost to manufacture one part	Euro/part
Number of product variants per application	Number of product variants that same the application is able to produce	Variants
Produced quantity	Number of parts that application produces within one day	Parts/day
Quality control cost per part	Average cost to control the quality of one part	Euro/part
Rework quantity	Number of parts that require (manual or automatic) rework	Parts/day
Selling price per part	Average price that a customer pays to acquire one part	Euro/part
Storage and transportation loss	Number of parts that get lost during storage or transportation within one day	Parts/day
Time to rework	Time required to perform (manual or automatic) rework of a single rework part	Hours/part
Total number of product variants	Total number of product variants that are offered and available for the customer	Variants

Table 3.2 Necessary technical and economic product data to be acquired

3.5.2 Process Data

Process data characterize quality and type of application. The strength of the presented framework is that the data can be collected independently of the production process. This means that, e.g., milling machines and autonomous guided vehicles can be evaluated using the same framework. While this approach offers the evaluation of a wide range of possible production processes, generalized data sets carry the danger that application-specific data is not collected, so that the framework might generate too unspecific results which must be validated in the future. Table 3.3 summarizes the necessary technical and economic process data to be acquired (sorted by alphabetic order).

Necessary Process Data	**Explanation**	**Unit**
Application downtime	Average time during which application is not available per day	Hours/day
Application setup time	Amount of time to make an application ready to produce a new batch	Hours/day
Average cost for training of new employee	Average cost for training of new employee to operate the application	Euro
Average number of shifts per day	Number of shifts per day a worker is involved in operating the application	Shifts/day
Batch Size	Number of parts that are manufactured in a production run	Parts/batch
Cost of cable harness	Sum of material cost to set up wired connections	Euro
Cost of controller	Average acquisition cost of one control unit or controller that is implemented into the application	Euro/controller
Cost of planned application downtime	Cost incurred from planned application downtime	Euro/hour
Cost of unplanned application downtime	Cost incurred from unplanned application downtime	Euro/hour
Cost of wired sensor	Average acquisition cost of one wired sensor that is implemented into the application	Euro/sensor
Cost of wireless sensor	Average acquisition cost of one wireless sensor that is implemented into the application	Euro/sensor
Hourly wage of application operator	Hourly wage of a worker, technician, or engineer who is responsible for operating the application	Euro/hour
Hourly wage of setup staff	Hourly wage of a worker, technician, or engineer who is responsible for setting up the application	Euro/hour
Lead time	Time between the initiation and completion of the production process to produce one part	Hours/part
Number of control units per application	Number of controllers or control units that application already uses to control the process	Controllers
Number of paths	The number of paths that an application can use to reach its goal; in case of flexible routing, the number is unlimited, otherwise, a value larger than one.	Paths

Number of setups	Number of setups within a time period	Setups/day
Number of wired sensors per application	Number of wired sensors that application already uses to sense the process	Sensors
Number of wireless sensors per application	Number of wireless sensors that application already uses to sense the process	Sensors
Personnel break time per shift	Personnel break time per shift	Hours/shift
Personnel work time per shift	Work time of personnel per shift (without a break) who is involved in operating the application	Hours/shift
Planned application downtime	Planned time during which application is not available per day	Hours/day
Planned application setup time	Planned time to make an application ready to produce a new batch	Hours/day
Planned lead time	Planned time between the initiation and completion of the production process to produce one part	Hours/part
Planned runtime per part	Planned time between two consecutive unit completions on the application	Hours/part
Planned transport time	Planned amount of time during which part is transported from one location to another	Hours/day
Runtime per part	Amount of time that elapses between two consecutive unit completions on the application	Hours/part
Total number of paths	Number of potential paths in the factory that the application could use under given infrastructure to reach its goal	Paths
Transport time	Amount of time during which part is transported from one location to another	Hours/day

Table 3.3 Necessary technical and economic process data to be acquired

3.5.3 Failure Data

Failure data characterize events that are neither planned nor desirable. Every failure causes additional time or cost expenses, so it is highly recommended to mitigate failure events. Table 3.4 summarizes necessary failure data to be acquired (sorted by alphabetic order).

Necessary Failure Data	**Explanation**	**Unit**
Average financial compensation cost per accident	Average cost incurred from financial compensation for an injured employee	Euro
Average material cost to repair application's failure	Average cost spent on material to repair the application after its failure	Euro
Average medical cost per accident	Average cost incurred from an injured employee	Euro
Cost for customer complaints	Average cost incurred from customer complaint (e.g., warranty cost, cost for gestures of goodwill, administration cost)	Euro/complaint

Hourly wage of repairment staff	Hourly wage of a worker who is responsible for repairing the application after application's failure	Euro/hour
Number of failure events caused by control system malfunctions	Number of failure events that are caused by application's control system malfunctions or failures	Failures/day
Number of failure events caused by mechanic failure	Number of failure events caused by mechanic failure such as leakage, overheat, loose attachments, failed brake system, …	Failures/day
Number of failure events caused by collision	Number of failure events that are caused by collision other moving or static objects or people	Failures/day
Number of failure events caused by disabled communication	Number of failure events that are caused by disabled communication	Failures/day
Number of failure events caused by wrong task execution	Number of failure events caused by wrong task execution such as unsuccessful loading, undesirable position accuracy, …	Failures/day
Number of failure events caused by wrong setup	Number of failure events caused by a wrong setup (e.g., too low or high speed, too low or high force, …)	Failures/day
Number of failure events caused by cyber attacks	Number of failure events caused by cyber attacks	Failures/day
Number of failure events for unknown reasons	Number of failure events that occurred without knowing the reason why it occurred	Failures/day
Number of application-caused accidents	Number of accidents caused by application's misbehavior	Accidents / year
Number of customer complaints per year	Number of customer complaints about quality issues regarding product or process	Complaints/year
Number of customer orders	Number of customer orders per year for products that are produced by the application	Orders/year
Number of delayed customer orders	Number of customer orders per year for products produced by the application and which do not arrive on time at the customer	Orders/year
Number of human-caused accidents	Number of accidents caused by human mistakes (e.g., striking one's head, falling down the stairs, …)	Accidents/year
Penalty cost for delayed order	Average cost incurred from delayed customer orders (e.g., penalty cost, cost for gestures of goodwill, administration cost, …)	Euro/order
Time between failure	Average time between two consecutive failure events of the application	Hours
$(\text{Time to repair})_{\text{Long-term}}$	Average time required to repair an application's failure (including ordering spare parts, waiting for service employees, …)	Hours
$(\text{Time to repair})_{\text{Short-term}}$	Average time required to repair an application's short-term failure	Hours

Table 3.4 Necessary technical and economic failure data to be acquired

3.5.4 Facility Data

Facility data refers to shopfloor layout and resource consumption of the application. Table 3.5 summarizes the necessary technical and economic facility data to be acquired (sorted by alphabetic order).

Necessary Facility Data	Explanation	Unit
Annual interest rate	Annual interest rate that is used for discounting future cash flows	% p.a.
Application lifetime	Expected lifetime of application in years to calculate economic key figures	Years
Compressed air consumption	Compressed air consumed by application within a day	Kilowatt-hour/day
Cost of compressed air	Cost of compressed air per kWh	Euro/kilowatt-hour
Cost of electric power	Cost of electric power per kWh	Euro/kilowatt-hour
Cost of gas	Cost of gas per British thermal unit (BTU)	Euro/BTU
Cost of water	Cost of water per liter	Euro/liter
Electric power consumption	Electric power consumed by application within a day	Kilowatt-hour/day
Facility maintenance cost	Daily maintenance cost per square meter to keep shopfloor in a good state (e.g., cleaning staff)	Euro/square meter per day
Facility rental cost	Rental cost per square meter	Euro/square meter per day
Gas consumption	Gas consumed by application within a day	British thermal unit/day
Location	Country where factory site is located	-
Manufacturing area	Area which is used to place machines or applications	Square meter
Rework area	Area which is used to rework parts and products	Square meter
Storage area	Area which is used to store spare parts, finished goods, …	Square meter
Total plant area	Total area of a production plant	Square meter
Water consumption	Water consumed by application within a day	Liter/day

Table 3.5 Necessary technical and economic facility data to be acquired

4 Quantification of 5G impact on data, KPI and goals

After setting up the basic model framework, the next step is to quantify the effect of 5G on production use cases. Therefore, on the one hand, the implementation of 5G as a communication tool enabling, e.g., faster tool changes, will be considered. On the other hand, the effects of technologies being enabled by 5G technology will be considered. Technologies that will be analyzed in this section are *condition-based monitoring* and *artificial intelligence*.

4.1 Direct 5G technology impact

In this chapter, possible "direct" impact of 5G on the use case and therefore its data is analyzed based on examples and literature. Direct impacts mean, that the influence as wireless network with high capabilities regarding e.g. latency and reliability (see without implementing any further technology is considered Probable impacts on the production process are summarized in Table 4.1 at the end of this section.

Product Data

Due to its described capabilities as communication network, 5G has an influence on the produced quantity (increase), scrap quantity (decrease), number of product variants per application (increase) and the percentage of individualized products (increase).

Due to its high reliability and availability, 5G technology is beneficial to enable both safe and efficient production processes, e.g. by wirelessly controlling AGVs or machine tools and enabling control loops that could not be realized before due to cable or network limitations. This reduces abrupt stoppages and short-term failures and enables stable production process. Thus, probability of produced quantity increases while probability of producing scrap is reduced. Furthermore, seamless integration of 5G will favor on-demand manufacturing [5GACIA2]. Being wireless and not limited to its factory location, machines can be relocated to corresponding production line so that additional manufacturing resources can be added [5GACIA2]. Machines can therefore be relocated for individual production program for each product variant which allows to manufacturing products directly according to customers' order [GEV20]. As a result, both number of product variants per application [Adi19] and percentage of individualized products increase [5GACIA1, EH20].

Process Data

In the category process data, 5G is expected to decrease the application set-up time, the unplanned application downtime and the lead time.

Each interruption of communication can cause system failures and downtime. 5G's high reliability assures consistent and continuous operation of applications that leads to safe, high-availability and uninterrupted processes. High availability and reliability of 5G communication technology and thus the process control facilitates high productivity of production lines. Whereas tools connected via e.g. Bluetooth or Wi-Fi are sensitive to interference, 5G connections are more stable [WG20]. Any transmission delay or failure can cause *unplanned application downtime* because task cannot be executed properly [5GACIA1], which is therefore decreased by 5G.

Furthermore, being a wireless technology, 5G facilitates reconfigurations and tool set ups. In case of e.g. tool change or damage, machine tools or robots need to be reconfigured. Resetting an industrial robot into a safe restarting position can cause several minutes of application setup time [5GACIA3]. 70% to 80% of installation costs resulting from cabling can be saved through using 5G [BOS+20]. Setting up wired connections is not only expensive but also time-consuming because each connection between machines and sensors must be carefully planned and tethered to a specific location. By using 5G, application setup time is reduced.

Failure Data

In the category failure data, 5G is expected to decrease the number of application-caused accidents, the number of delayed customer orders and the time to repair.

Wired connections usually work reliably but in case of failure, it might be hard to find the failure cause. Unplugged cables are easy to detect but detection of cable breakage is often based on assumptions. By using wireless connections, it will probably become easier to repair because it will not be necessary any more to examine the whole wiring harness. Instead, the replacement of affected sensors will be sufficient. In this way, time to repair decreases [BOS+20].

For certain safety functions, transmission time under 1 ms are required [5GACIA3]. 5G with Ultra Reliable Low Latency Communication (URLLC) features can fulfill this requirement and is therefore an appropriate communication technology for safety installations to minimize the number of application-caused accidents.

For manufacturing industry, cyber-attacks can lead to fatal consequences such as reduced earnings through lost customer trust, delayed product’s launch, or increased warranty costs [AC19]. In 2019, more than 20% of the companies surveyed have been victim of a cyber-attack on their smart manufacturing initiatives [EH20]. Cisco expects number of cyber-attacks to grow by 14% per year with over 20% of the attacks greater than 1 Gbps which is enough to take most organizations completely offline [CIS20]. As a result, the number of failure events caused by cyber-attacks is expected to grow which is why Industry 4.0 solutions, including 5G networks must integrate security mechanisms.

Data Category	Data	Potential Impact	Source
Product data	Produced quantity	Increase	[Adi19]
	Scrap quantity	Decrease	[Adi19]
	Number of product variants per application	Increase	[Adi19]
	Percentage of individualized products	Increase	[5GACIA1] [EH20]
Process data	Unplanned application downtime	Decrease	[5GACIA3]
	Application setup time	Decrease	[BOS+20]
Failure data	Number of application-caused accidents	Decrease	[5GACIA3]
	Number of cyber-attack-caused accidents	Increase	[AC19]
	Time to repair	Decrease	[BOS+20]

Table 4.1 Potential impacts of 5G technology on application

4.2 Impact of 5G-enabled technologies

In this chapter, possible ”indirect” impact of 5G on the use case and therefore its data is analyzed based on examples and literature. This means that this section goes beyond the direct improvement of the considered application via 5G but also takes into consideration the effects of additional technologies being enabled by 5G . Technologies that will be analyzed in this section are *condition-based monitoring* and *artificial intelligence*.

4.2.1 5G-enabled technology 1: condition-based monitoring

The goal of condition-based monitoring (CBM) is to increase the safety, precision, and efficiency of applications [YSJ+20]. Condition-based monitoring builds the basis for implementing machine learning models, for example, to predict maintenance [YSJ+20]. Precise monitoring and control mechanisms are based on a high degree of integration into a manufacturer's core processes [Adi19]. While 5G has the potential to enable real-time monitoring, it is equally important to figure out which data must be monitored to achieve higher safety, precision, and efficiency. Designing IoT systems includes selecting sensor devices, communication protocols, data storage, and computation appropriate for the application [MMH+20]. Data relevant for CBM range from monitoring single machine components and their conditions to monitoring the behavior of complete transportation systems.

Wireless sensor networks require interfaces and protocols for several nodes supporting sensors and actuators capable of sensing, controlling, computing, and communicating [ZZ07]. Several sensors monitor the current state or behavior of the manufacturing environment and thus, form a distributed monitoring system [5GACIA2]. Massive machine-type communication by 5G will support massive wireless sensor networks by enabling wireless connection of much more devices than today [5GACIA2]. The advantage of 5G for condition-based monitoring is its high network reliability that ensures online monitoring processes [YSJ+20]. For less demanding tasks, computation can be located in a central cloud server [SPY+20b].

4.2.1.1 Technical Analysis

In the following, the effect of implementing condition-based monitoring on an application is analyzed. At the end of this chapter, the effects are summarized in Table 4.2. Condition-based monitoring has an impact on production planning because it allows complete transparency of the current production status. Schedule and product changes can be quickly communicated to the machine [WG20]. Kearney estimates that identifying bottlenecks in real-time via dashboards leads to dynamic optimization of production schedules and a lead time reduction of 35% to 50% [MPA21]. The Kennametal factory implemented IoT sensors to monitor manufacturing machines and reduced application setup times by 50% so that the produced quantity increased while using the same number of machines [MPA21]. 5G allows to increase the number of connected devices and thus allows to provide a more detailed view of machine status, processes, and systems [Adi19]. A system that steadily provides data on the health of its products and machines allows workers to identify process flaws quickly. As a result, time to search for causes of failure is decreased, resulting in reduced time to repair. Furthermore, unnecessary maintenance is avoided when maintenance and repair tasks are performed on a just-in-time basis [BOS+20]. Understanding manufacturing processes using sensor data helps to identify bottlenecks and optimization potential, which is why increased productivity is expected from the use of 5G [Adi19]. STL partners guess that productivity and, thus, produced quantity can increase by approximately 10% to 15% [Adi19].

Condition-based monitoring will raise the companies' awareness of their consumption behavior [MMH+20]. 40% of energy in buildings relates to air conditioning systems [MMH+20]. In a smart factory, temperature sensors can signal air conditioning systems to turn on or off ventilation or cooling systems to save energy [MMH+20]. 15% of total electricity usage in buildings relates to lighting [MMH+20]. In a smart factory, light sensors receive changes in ambient light and can automatically dim the light levels [MMH+20]. Motion sensors which are also called passive infrared sensors, measure infrared light radiation emitted from humans and objects [MMH+20]. Sensors can automatically turn off the lights or air conditioning systems in case of no movement detection [MMH+20]. By equipping application components with sensors, detecting components that use more energy than their nominal energy level is possible [MMH+20].

In conclusion, it will become easier to detect wasted energy so that process changes towards reduced electric power consumption, reduced compressed air consumption, reduced gas consumption, and reduced water consumption can be implemented and validated. Furthermore, reduced energy consumption due to lower power IoT devices and long battery lifetimes of up to 10 years will reduce costs of maintaining devices and energy consumption [Adi19]. The impact of condition-based monitoring on applications is summarized in Table 4.2.

Data Category	Data	Potential Impact	Source
Product data	Produced quantity	Increase by 10-15%	[Adi19] [MPA21]
	Storage and transportation loss	Decrease	[BOS+20]
Process data	Unplanned application downtime	Decrease	[WG20]
	Application setup time	Decrease by 50%	[MPA21]
	Lead time	Decrease by 35% to 50%	[MPA21]
Failure data	Number of failure events caused by wrong task execution	Decrease	[BOS+20]
	Number of failure events caused by wrong setup	Decrease	[BOS+20]
	Time to repair	Decrease	
Facility data	Total energy consumption	Decrease by 2%	[WG20]
	Electric power consumption	Decrease	[AND16] [MMH+20] [Adi19]
	Compressed air consumption	Decrease	
	Gas consumption	Decrease	
	Water consumption	Decrease	

Table 4.2: Potential Impact of Condition-Based Monitoring on Application

4.2.1.2 Economic Analysis

The major costs for condition-based monitoring result from wireless sensor networks, including sensors and complete network infrastructure, to collect relevant data. Condition-based monitoring requires unique identification of machines and objects. Beside wireless sensor networks and RFID technology, monitoring devices must be installed on the shopfloor to display measured data. Monitoring devices are tablets, smartphones, or any other screens that make data visible for workers, technicians, and engineers. It is assumed that costs for acquiring components for condition-based monitoring are incurred once at the beginning of application lifetime. Therefore, it is accounted for CAPEX. In this framework, according to [BLA+18], it is estimated that acquisition $\text{cost}_{\text{Wireless Sensor Network}}$ is 36,000 Euros. Acquisition $\text{cost}_{\text{RFID Technology}}$ is estimated to be 10,000 Euros, and acquisition $\text{cost}_{\text{Display Device}}$ is supposed to be 3,000 Euros. This results in initial investment costs of 49,000 Euros for implementing condition-based monitoring. These costs must be validated in the future.

It is expected that costs for components storing processing power, memory size, and network capacity will decrease whereas their capacity increases [BLA+18]. Cost of IoT sensors is expected to reduce by 10% from 2020 to 2022 [MPA21]. Investment in condition-based monitoring is calculated by Equation (6):

$$CAPEX_{CBM} = Acquisition\ Cost_{Wireless\ Sensor\ Network} + Acquisition\ Cost_{RFID\ Technology} + Acquisition\ Cost_{Display\ Device} \quad (6)$$

Additional costs arise from maintaining *condition-based monitoring.* Maintenance includes installation of additional sensors, updating software programs, and keeping technology in good condition. Maintenance costs are regular outgoing cash flows which mainly arise from personnel costs. The responsible employee is called CBM maintainer. This framework assumes that only one CBM maintainer is required to maintain *condition-based monitoring* for one application. The yearly wage of a CBM maintainer is estimated to be 60,000 Euros per year. Personnel requirements might rise when more applications are connected.

Outgoing cash flow is calculated by *Equation (7):*

$$OPEX_{t,\ CBM} = Wage_{CBM\ Maintainer} \cdot Number\ of\ CBM\ Maintainers \quad (7)$$

4.2.2 5G-enabled technology 2: Artificial intelligence and machine learning

In traditional factories, data is often only used to manipulate the current process [GEV20]. Data is not stored in the long term for cost reasons and conserve network capacity, especially at field level [GEV20]. In smart factories, 5G will provide cloud-based solutions that allow the storage of large amounts of data. In this way, data collected during condition-based monitoring may become valuable for the future. Data can be supplemented with additional information by workers and become even more valuable for further analyses in quality assurance or predictive maintenance [GEV20]. This paves the way for artificial intelligence and machine learning models (AI & ML models). The AI systems market is expected to grow by 28% per year from 2018 to 2025 [MPA21].

Machine learning is a subgroup of artificial intelligence. Machine learning models transform data into information. Predictive maintenance is one of the most known applications. [Adi19] provides detailed insights into this: In traditional factories without predictive maintenance, machine failure causes a series of actions. First, production stops, and technicians or engineers assess the problem. In the next step, spare parts are ordered, and after delivery of parts, the technician conducts the repair on-site. Scheduled maintenance visits help to keep machines in good condition. However, planned machine downtimes are required for each maintenance visit. In addition, unnecessary maintenance and repair costs arise even if that machine did not require any maintenance. Predictive maintenance aims to optimize maintenance processes. Machines are equipped with several sensors to measure current conditions. Evaluation of parameters helps to predict the need for repairments or machine breakdown ahead of time.

A drawback of existing machine learning models is that benefits are not materialized yet. On the one hand, it is challenging to integrate information from operational technology into IT systems such as ERP systems. On the other hand, ML platforms are not mature enough to effectively predict outcomes because too few variables are measured yet. Therefore, 5G can enhance machine learning models by increasing the number of data sources through mMTC, and this way increasing the amount of data. In the future, more sensors can measure different parameters reliably and in real-time. A single data point might be the reason for malfunction, so low latency and high reliability increase the probability of detecting this single point. Furthermore, data analysis will be enhanced by cross-referencing current data with historical data and providing trends to predict results.

4.2.2.1 Technical Analysis

I In the following, the impact of *artificial intelligence and machine learning models* on an application is analyzed. At the end of this chapter, effects are summarized in Table 4.3.

The accuracy of simulation models is affected by the number of sensors recording the process and the data quality. Both factors can be enhanced through 5G. On the one hand, 5G wireless sensors are easier to install and more flexible to set up. On the other hand, time synchronization of several 5G sensors is enhanced [SWA+19] to extract more detailed information from sensor data. Simulation processes with more accurate digital models lead to more accurate simulation results [SWA+19]. Simulation results equal to actual results in the real world allow more advanced planning processes. Finally, data quality is vital for valid results and decides on the accuracy of planned production capacities [BLA+18]. For example, the candy company Hershey's implemented IoT sensors and machine learning algorithms to better predict the final net weight of the product [MPA21]. By getting closer to the precise weight, product giveaways could be minimized, and efficiency could be increased [MPA21].

To meet customer's expectations of zero defects, manufacturers tend to inspect 100% of produced quantity because sample testing is not sufficient anymore [EH20]. 45% of surveyed companies agree that application operators spend 33% of the time watching inspection machines [EH20]. Machine learning algorithms can speed up quality control processes, reduce the need for human involvement, and therefore decrease quality control cost per part. Automation of quality control supported by 5G is examined by Volkswagen [BOS+20]. Volkswagen wants to install private industrial 5G mobile networks in 122 factories [BOS+20]. It estimates that the implementation of 5G ultrasonic door weld inspections will result in annual cost savings of 3 million EUR [BOS+20]. ML algorithms can be trained by collecting defects over time, learning which parts are scrap, which parts are good, and which machine can optimally rework the part. As a result, only parts that are really scrapped will be rejected as scrap, which might result in less scrap quantity. In fully automated operations, 5G's URLLC enables real-time monitoring of product attributes allowing the machine to adapt parameters in near real-time.

This becomes especially important for critical manufacturing processes in terms of vibration, acoustics, temperature, tolerances, or pressure [AND16]. Losing a whole production lot due to incorrectly set parameters becomes less probable when the production process is continuously monitored. As a result, first-time good quantity increases while scrap and rework rates become reduced. STL partners estimate that scrap quantity is reduced by 10% by adapting processes in real-time [Adi19].

As ramp up time decreases, the production process reaches its maximum speed faster. Siemens operates a smart factory, the Amberg factory, to show the impact of advanced analytics of data generated by IoT devices. For an application with an automation level of more than 75%, production capacity has increased eight times [ZYY+19]. Kearney estimates that data-based analytics lead to a better understanding of asset performance so that the yield potentially increases by 50% to 60% [MPA21].

Predictive and preventive maintenance methods help manufacturers perform small machine adjustments when machines do not work perfectly [Adi19]. For machine tool monitoring, latencies below 10ms are required to take effective actions on time [Adi19]. As a result, due to the low latency of 5G, the number of failure events caused by wrong task execution and the number of failure events caused by collisions can be decreased through early detection of inconsistencies in the production process. Effective data analysis also means that maintenance can be carried out more precisely and in less time so that the time to repair decreases [TMK19]. Reduced maintenance time will further save workforce time [TMK19]. In this way, unplanned application downtimes can be decreased, and the asset uptime increases. According to [Adi19], unplanned downtime due to machine failure causes a loss of approximately 4.6 % of planned production time. This is relevant because unplanned application downtimes can be up to nine times more expensive than planned application downtime.

Data Category	Data	Potential Impact	Source
Product data	First time good quantity	Increase	[AC19][AND16]
	Rework quantity	Decrease by 10%	[AC19][AND16] [EH20]
	Scrap quantity	Decrease by 10%	[Adi19][EH20]
	Produced quantity	Increase	[AC19][ZYY+19]
	Quality control cost per part	Decrease	[Adi19][BOS+20]
Process data	Unplanned application downtime	Decrease by 6% to 8.7%	[Adi19]
	Planned runtime per part	Decrease	
Failure data	Number of failure events caused by mechanic failure	Decrease by 10%	[EH20]
	Number of delayed customer orders	Decrease	[Adi19]
	Number of failure events caused by collision	Decrease	[Adi19]
	Number of failure events caused by wrong task execution	Decrease	[Adi19]
	Time to repair	Decrease	[TMK19]

Table 4.3: Potential impact of AI & ML models on application

4.2.2.2 *Economic Analysis*

As soon as a wireless sensor network is installed, a high amount of captured data needs to be analyzed and put into context to implement self-learning algorithms. This is mainly performed by human workers, the so-called data scientists. Market research shows that it will be beneficial for most manufacturers to have an in-house data scientist team to maintain solutions over the lifetime of an application [MPA21]. The personnel cost of data scientists is not a single investment but a periodic outgoing cash flow in every period *t.* Cash flow is calculated by Formula (8):

$$OPEX_{t,\ AI\ \&\ ML\ Models} = Wage_{ML\ Practitioner} \cdot Number\ of\ ML\ Practitioners \quad (8)$$

This report assumes that two data scientists are required to effectively implement *artificial intelligence and machine learning models* for one application. The yearly wage of data scientists is assumed to be 80,000 Euros. The quality of ML models depends on the quality of data and experience of the data scientist.

5 Model implementation

In this section the implementation of the model is explained. The model builds on the previous presented framework (*chapter 3*) and 5G's impact on the data, KPI and goals (*chapter 4*) to evaluate the potential of 5G. The tool will be made accessible via 5G-SMART's website (https://5gsmart.eu). The user interface is shown in *Figure 5.1.* The user interface depicts the overall framework architecture, which is described in *chapter 3.2.*

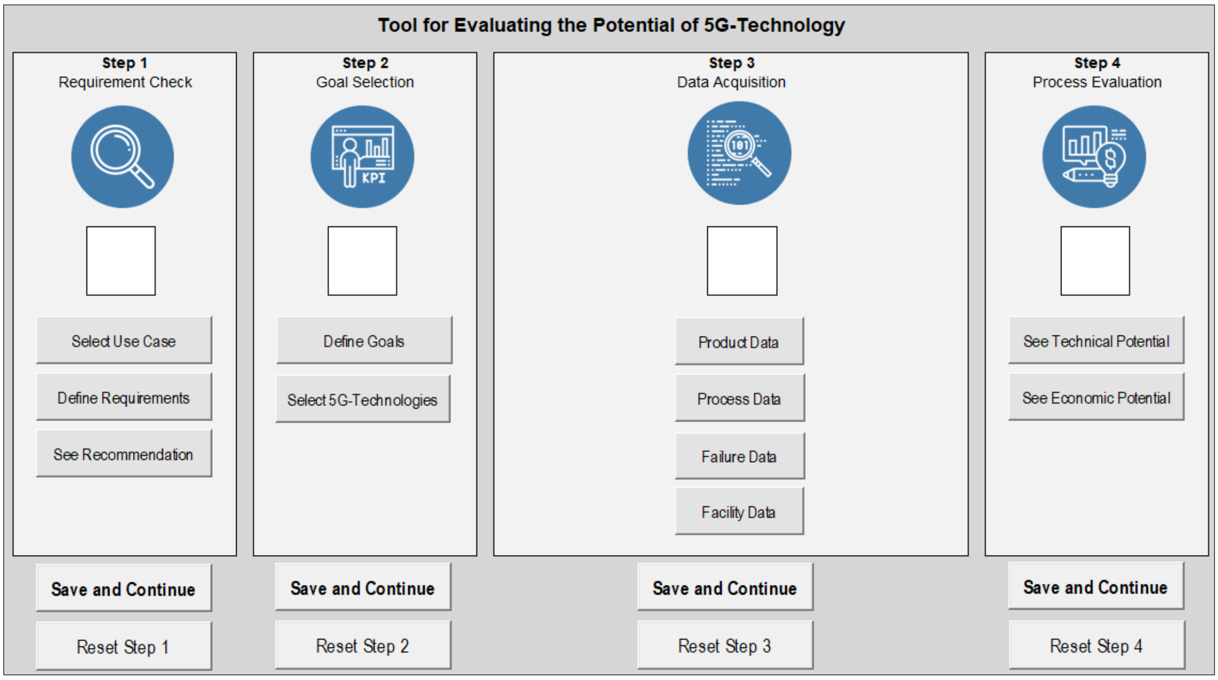

Figure 5.1: User interface of 5G evaluation tool

Step 1 includes the use case selection. Here, the model user can select one of the following use cases, as shown in *Figure 5.2*. For each use case, a short description is given to guide the user to the proper use case.

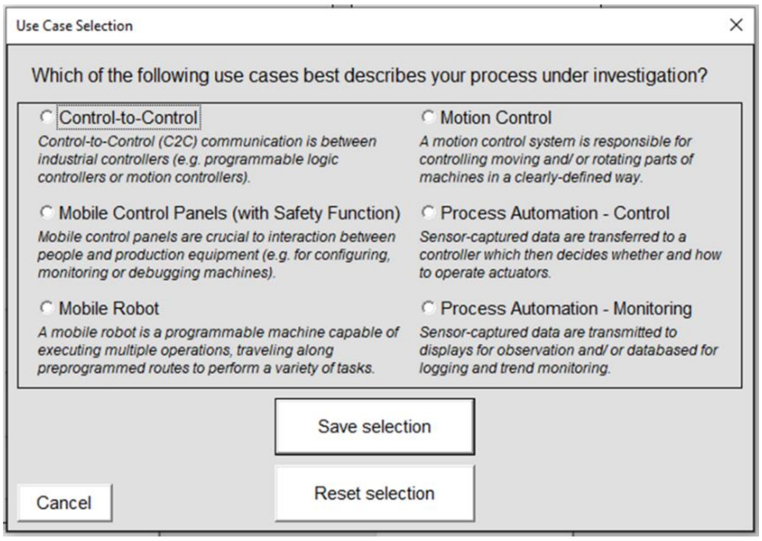

Figure 5.2: Use case selection

Step 1 also includes entering the values for network requirements for the application as shown in *Figure 5.3.* The user is asked to estimate the required latency, reliability, availability, data rate, connection density, localization precision, communication range, and mobility of the application.

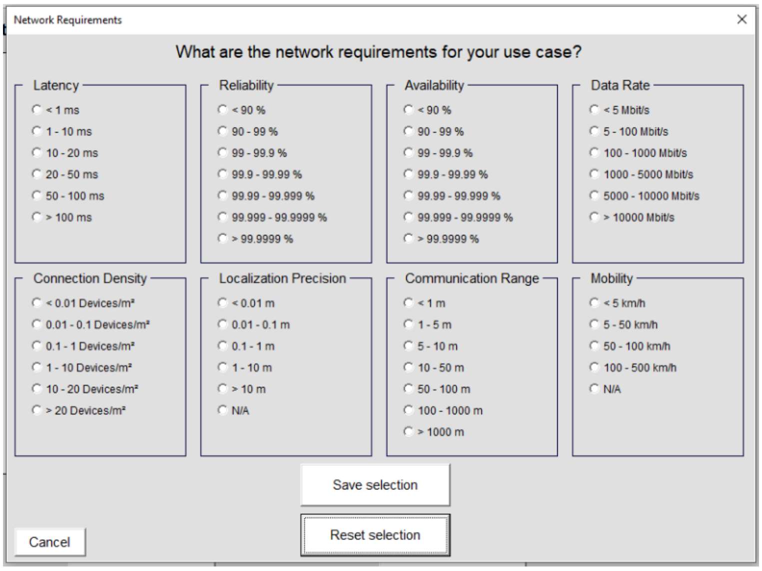

Figure 5.3: Definition of network requirements for application

Based on the entered network requirements, a recommendation is given indicating which communication technologies would meet the requirements. The user interface for this step is shown in *Figure 5.4*. In case that 5G is not required for the application, the user gets a message that the model might not be the right one.

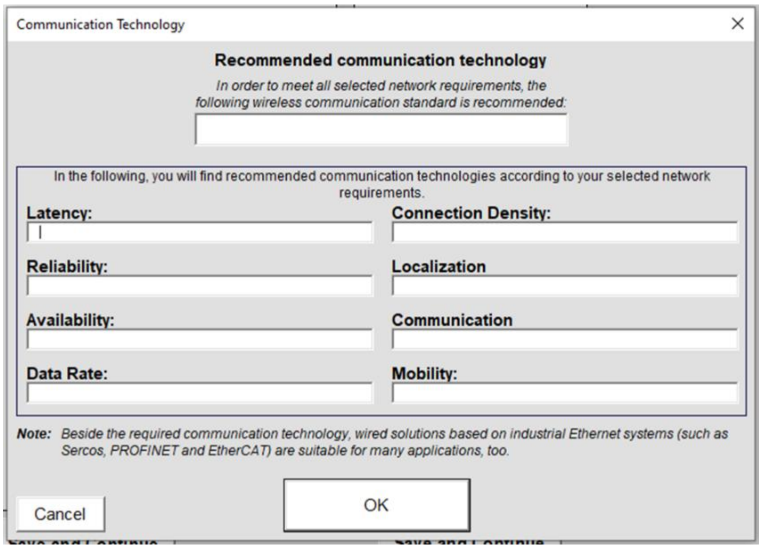

Figure 5.4: Recommendation of communication technology

In step 2, technical and economic goals are determined by the user, as *Figure 5.5* shows. Based on *chapter 0,* seven technical goals and two economic criteria can be selected. It is possible to select more than one goal at a time. Based on the selected goals, the user is asked in step 3 to enter the data necessary to evaluate the goals selected so that no "unnecessary" data need to be entered in the tool.

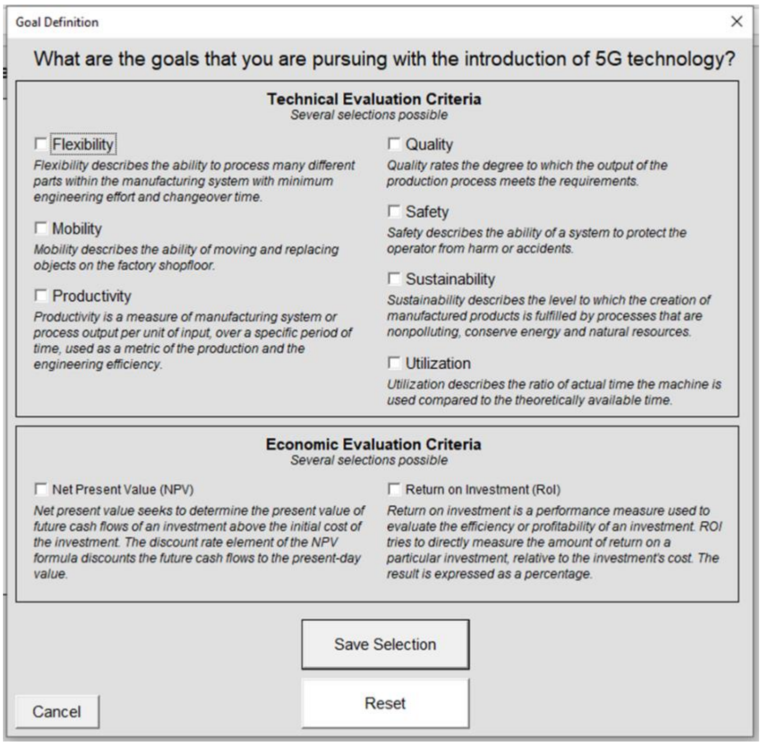

Figure 5.5: Definition of technical and economic goals

In a next step, the user can choose whether it is planned to implement any additional 5G-enabled technology or not as shown in *Figure 5.6.* In the tool it is possible to choose two additional 5G-enabled technologies. Each technology is briefly explained. The enabled technologies are not mandatory to choose.

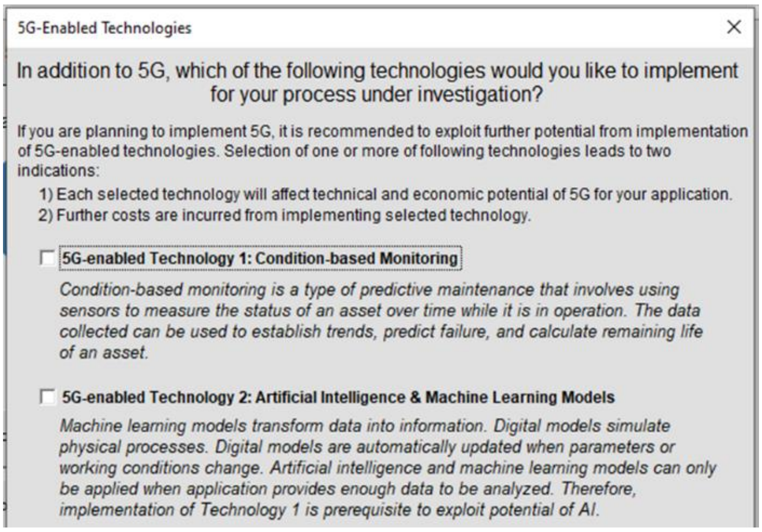

Figure 5.6: Selection of 5G-enabled technologies

In step 3, data is acquired. When the user clicks buttons labeled *Product Data*, *Process Data*, *Failure Data*, or *Facility Data*, a *UserForm* for technical data opens up. *Figure 5.7* shows an example of how data is entered. The user can select either day, week, month, or year. If a time unit other than a year is selected, cash flows are scaled up linearly to one year to determine the economic potential in terms of NPV and RoI. For each data, a short description is given so that the user easily understands its meaning.

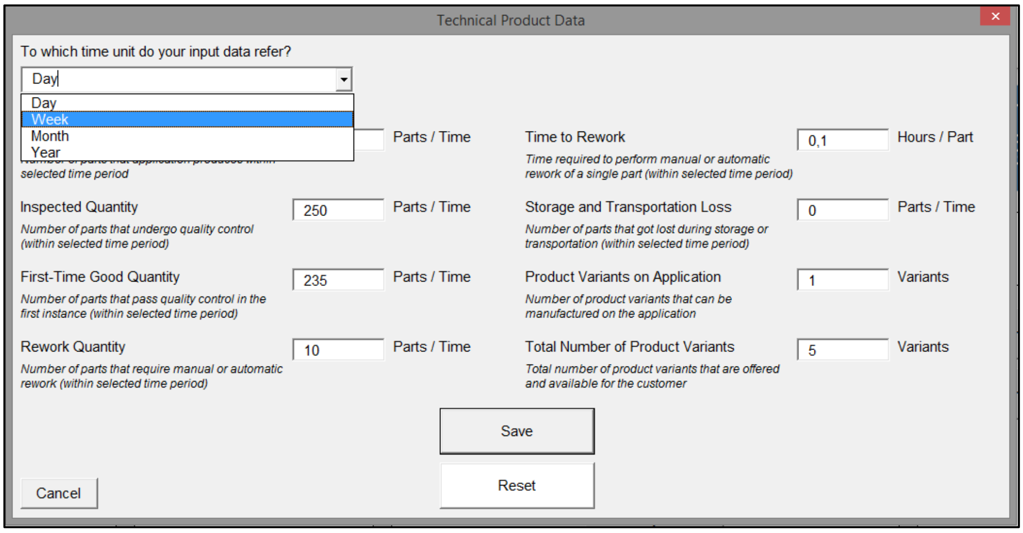

Figure 5.7: Userform for technical product data

Figure 5.8 shows how the options of human involvement are in the framework. The user is asked if the use case requires any human involvement

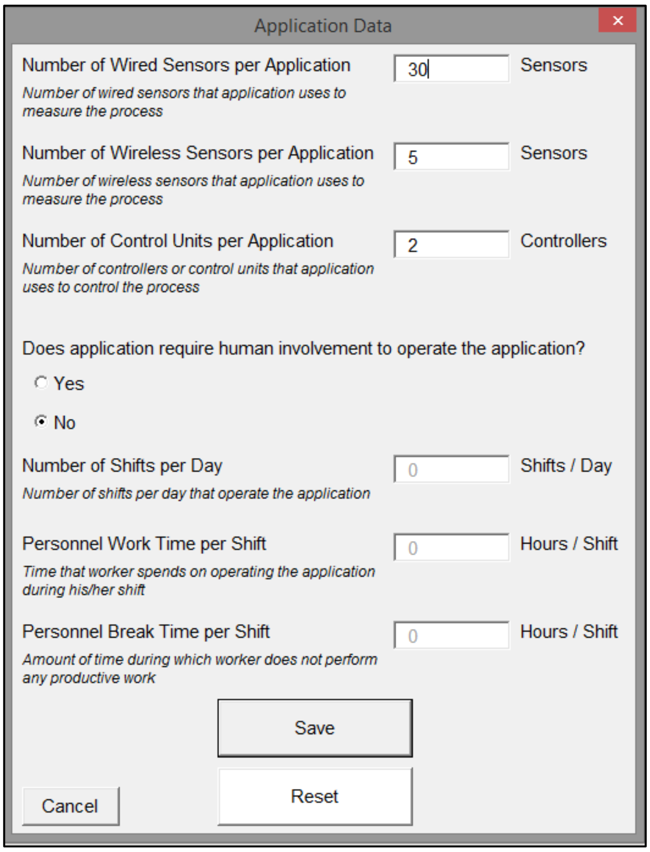

Figure 5.8: Entry of use case data

Other data concerning economic evaluation is acquired as shown in *Figure 5.9*.

Figure 5.9: User Form 8 – Acquisition of Other Data

The selection of country determines the energy convergence factor. Depending on the energy mix of a country, a different amount of CO_2 is emitted. By now, only European countries can be selected. While Sweden has the most ecological energy mix with a convergence factor of 0.000013 kg CO_2 per Wh, Estonia's energy mix is less ecological, with 0.000819 kg CO_2 per Wh. Conclusively, Estonian's carbon footprint is 63 times higher than Sweden's footprint when the same energy is consumed. Furthermore, the user can select the expected application lifetime to calculate depreciation and NPV. Lifetime ranges between one year and ten years. For the economic analysis, the applied interest rate is relevant. As shown in *Figure 5.9*, the user can select any interest rate between 1% p.a. and 10% p.a.

After saving step 3, the user can see the technical and economic potential of 5G for his/her application in step 4. A graphical representation of technical and economic goals is displayed.

6 Application of evaluation model

This section serves to demonstrate the working principle of the developed evaluation model. As an example, the model is applied to evaluate the potential of 5G for the use case of Autonomous Guided Vehicles (AGV) in manufacturing industry, which was designed based on discussions with ABB and Bosch.

The route of an AGV is illustrated in Figure 6.1. The task of AGVs is the transport of goods. AGVs are typically guided by either markings or wires in the floor. 5G connected vehicles can however also be guided by their own sensors and cameras [5GACIA2]. In case of obstacles like moving objects or workers, the AGV must be able to adapt its route abruptly to avoid collisions. In 2017, BASF already installed a testbed for a fleet of automated guided vehicles connected via 5G [GEV20]. In addition to extensive sensor technology, connection to control center is also crucial as high data rates and short guaranteed packet delay would even allow remote control of AGVs via a control center [GEV20]. It is possible to offload complexity from AGV to edge computing [GEV20]. All safety-related functions must be processed and executed in the vehicle itself [GEV20]. In accordance with [GEV20], condition-based monitoring is implemented for this use case.

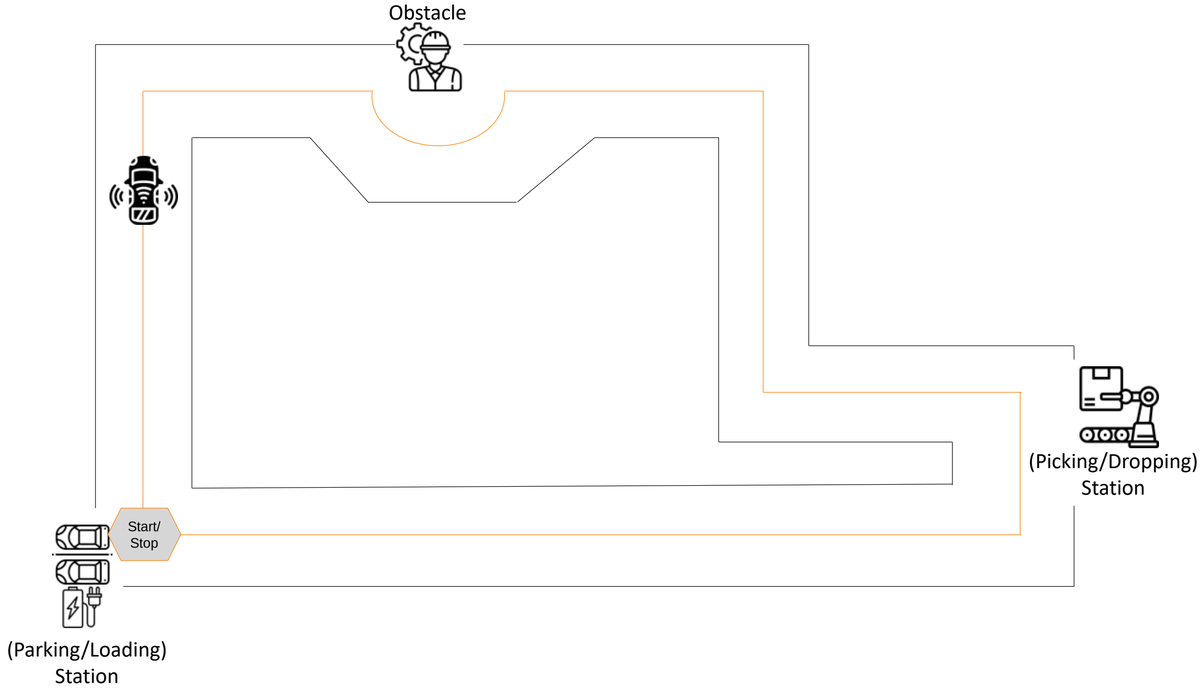

Figure 6.1 Use case description

In step 1, the use case is allocated to one of the six presented use cases provided by the tool, shown in Figure 6.2. AGVs are a widespread subgroup of mobile robots. Mobile robots are machines that can move autonomously. Their tasks reach from simple transport of goods to complex human machine interactions. Their superiority over traditional industrial robots is their ability to sense and react to their environment. Sensor data is transmitted by guidance control systems and exchanged between machines to avoid collisions, assign tasks, or manage robot traffic [5GACIA2].

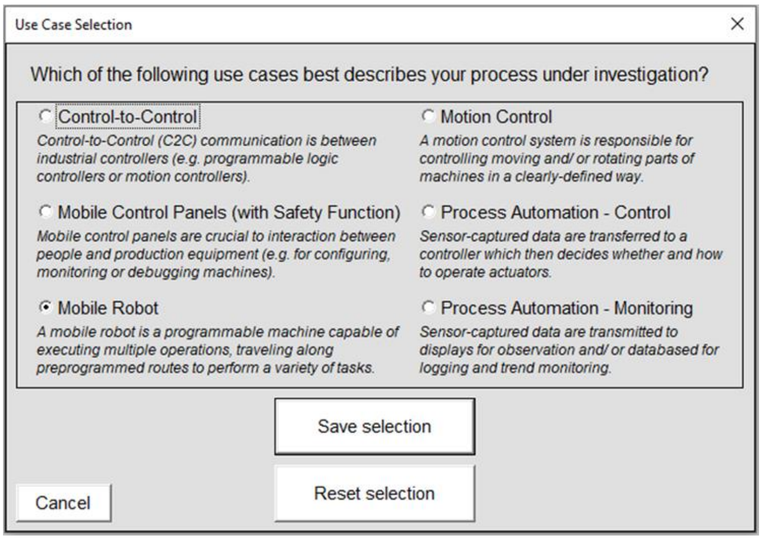

Figure 6.2 Use case selection for AGV

In the next step, network requirements for an exemplary AGV are picked to check the necessity of 5G. Selected network requirements for this example are shown in Figure 6.3 based on literature and workshops. The data rate required for mobile robots equipped with a video camera for video streaming has the highest demands [5GACIA2]. For deterministic traffic, the data rate is assumed to be 10 Mbit/s [5GACIA2]. Remote tactile control using augmented reality is assumed to require reliability of 99.9999% and a latency of 0.5 ms. For the considered AGV, reliability must be greater than 99.9%, with latency between 5 ms to 10 ms [SYJ19]. For connecting up to 10,000 devices or vehicles per square kilometer, real-time communication requires a refresh rate of 0.33 seconds [BONT20]. Precise position localization is especially important for AGVs [5GACIA2]. Accuracy should be below 20 cm while supporting velocities up to 30 km/h [5GACIA2].

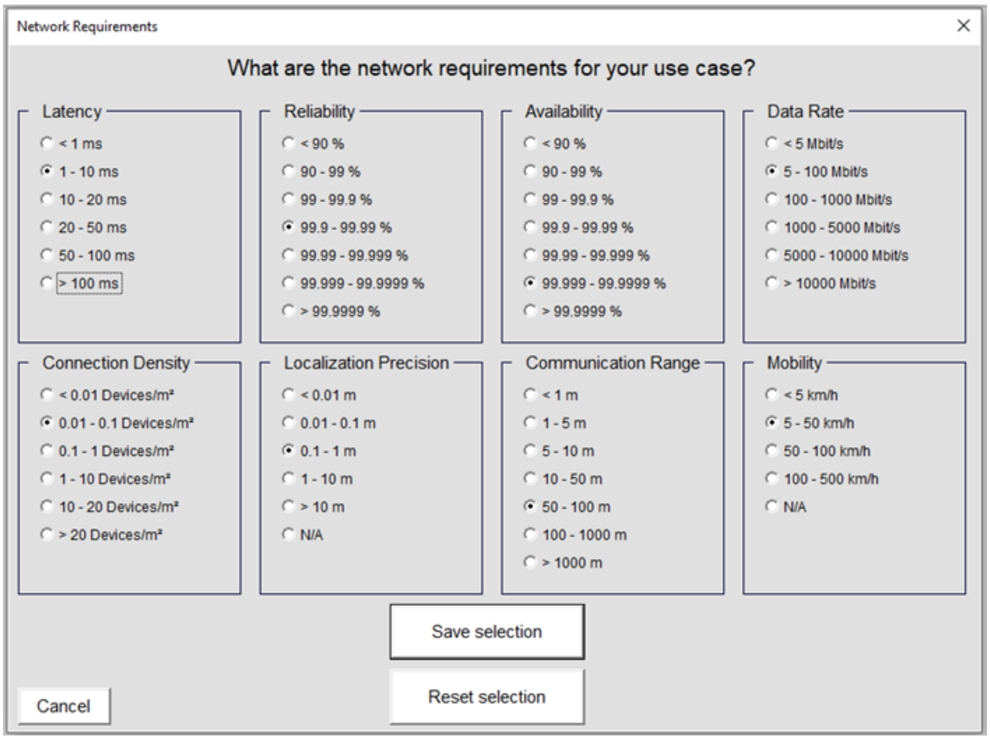

Figure 6.3 Definition of requirements for AGV use case

The model compares defined network requirements with existing wireless standards. As a result, the user gets a recommendation for communication technologies that fulfill the specifications. As shown in Figure 6.4, 5G is the only communication technology that achieves the needed high availability and high localization precision of the example use case considered. Therefore, to meet all selected network requirements, 5G is recommended for this AGV application.

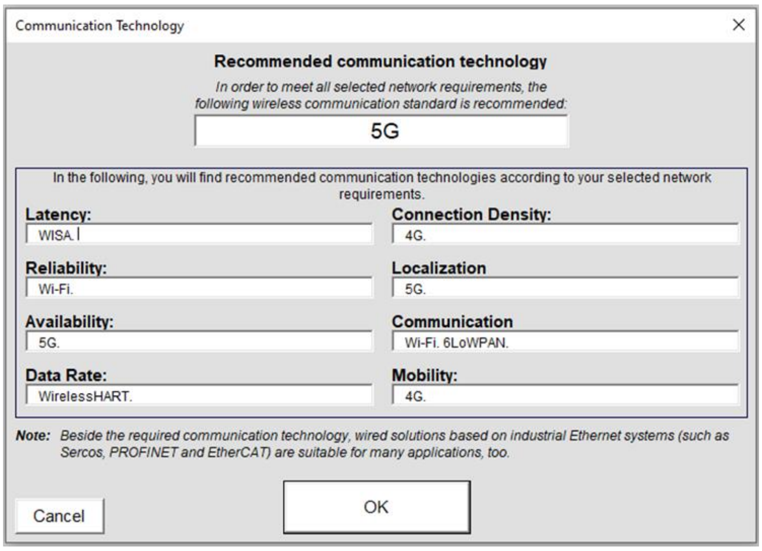

Figure 6.4 Recommendation of ICT for the AGV use case

The next step will be to decide which additional 5G-enabled technologies should be implemented. For the AGV application, technology 1 is selected as shown in Figure 6.5. Several sensors that are located on the AGV itself and on the shopfloor measure current condition which is why condition-based monitoring provides further information on AGV's surroundings. Measured values are uploaded over the communication network. Global navigation system is connected to host computer and includes systems such as route planning systems or AGV management systems.

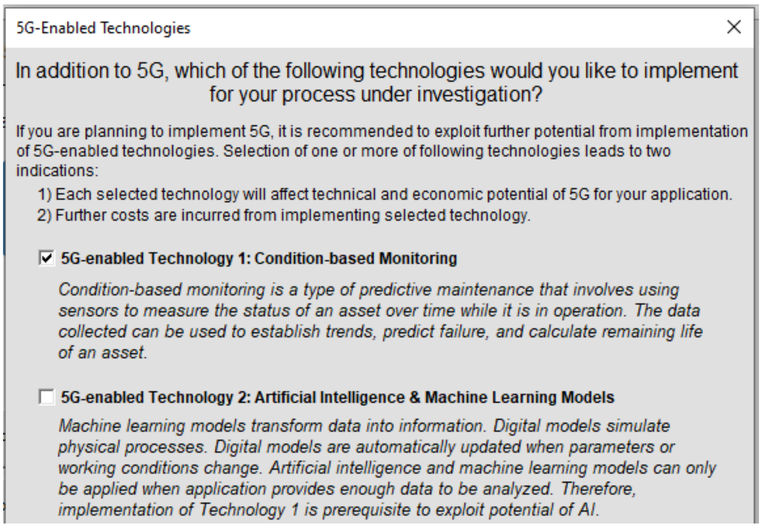

Figure 6.5 Selection of 5G-Loops

In the next step, the goals to be evaluated are defined as shown in Figure 6.6. The potential of 5G technology for AGV applications is evaluated for seven technical goals (flexibility, mobility, productivity, quality, safety, sustainability, and utilization) and two economic goals (net present value, return on investment).

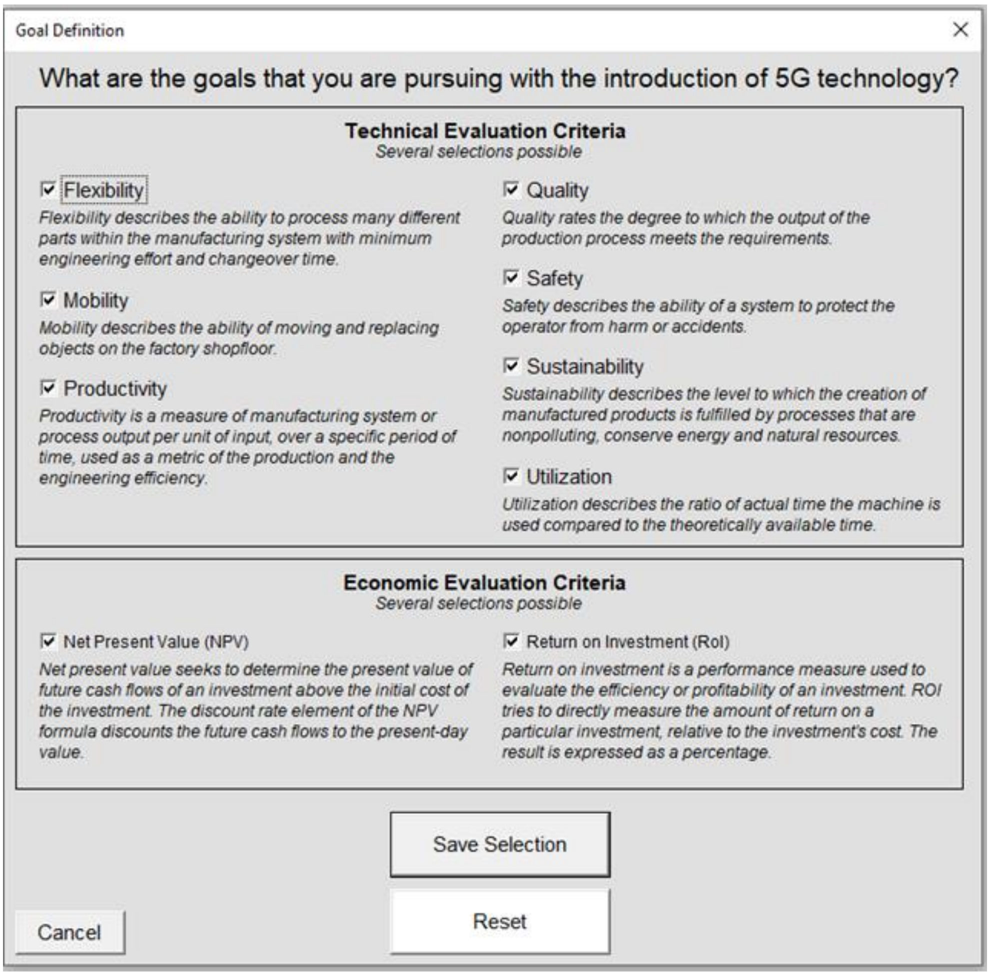

Figure 6.6 Selection of Technical and Economic Goals

Step 3 includes data acquisition concerning product, process, failure and facility data. After the data is entered, the model determines the 5G potential of the application. Underlying assumptions are summarized in Table 6.1. The quantitative impact is estimated based on literature and expert knowledge. In case that data is affected by more than one technology, individual impact is summarized. For example, *application setup time* decreases by 5% through *condition-based monitoring* and by 8% through wireless nature of 5G. If a company decides to implement 5G without implementing *condition-based monitoring*, *application setup time* will only decrease by 8%. Otherwise, *application setup time* reduces by 13%.

Table 6.1 Literature and expert workshop based potential impact of 5G technology and condition-based monitoring on AGV Application

Affected Data	Technology	Quantitative Impact
Application setup time	5G technology	Decrease by 8%
	Condition-based monitoring	Decrease by 5%
Electric power consumption	Condition-based monitoring	Decrease by 1%
	Edge computing	Decrease by 1%
First time good quantity	5G technology	Increase by 2%
Number of application-caused accidents	5G technology	Decrease by 100%
Number of delayed customer orders	5G technology	Decrease by 10%
Number of failure events caused by control system malfunctions	5G technology	Decrease by 95%
Number of failure events caused by cyber attacks	5G technology	Increase by 14%
Number of failure events caused by disabled communication	5G technology	Decrease by 99%
Number of failure events caused by wrong task execution	Condition-based monitoring	Decrease by 10%
Number of failure events caused by wrong setup	Condition-based monitoring	Decrease by 20%
Number of paths	Edge computing	Increase by 600%
Number of product variants per application	5G technology	Increase by 200%
Percentage of individualized products	5G technology	Decrease by 5%
Produced quantity	5G technology	Increase by 2%
	Condition-based monitoring	Increase by 2%
Storage and transportation loss	Condition-based monitoring	Decrease by 2%
Time to repair	5G technology	Decrease by 2%
	Condition-based monitoring	Decrease by 4%
Total energy consumption	Condition-based monitoring	Decrease by 2%
Unplanned application downtime	5G technology	Decrease by 1%
	Condition-based monitoring	Decrease by 3%

Finally, the user can see the results shown in Figure 6.7 to Figure 6.12. In Figure 6.7, the overview of the evaluation of the technical goal criteria is given. For the investigated AGV application, the major potential is expected from increased flexibility (+49.0%), mobility (+54.1%) and safety (+14.2%). On top of that, minor improvements in productivity (+4.3%) and sustainability (+3.9%) are expected while there is no significant impact on quality and utilization.

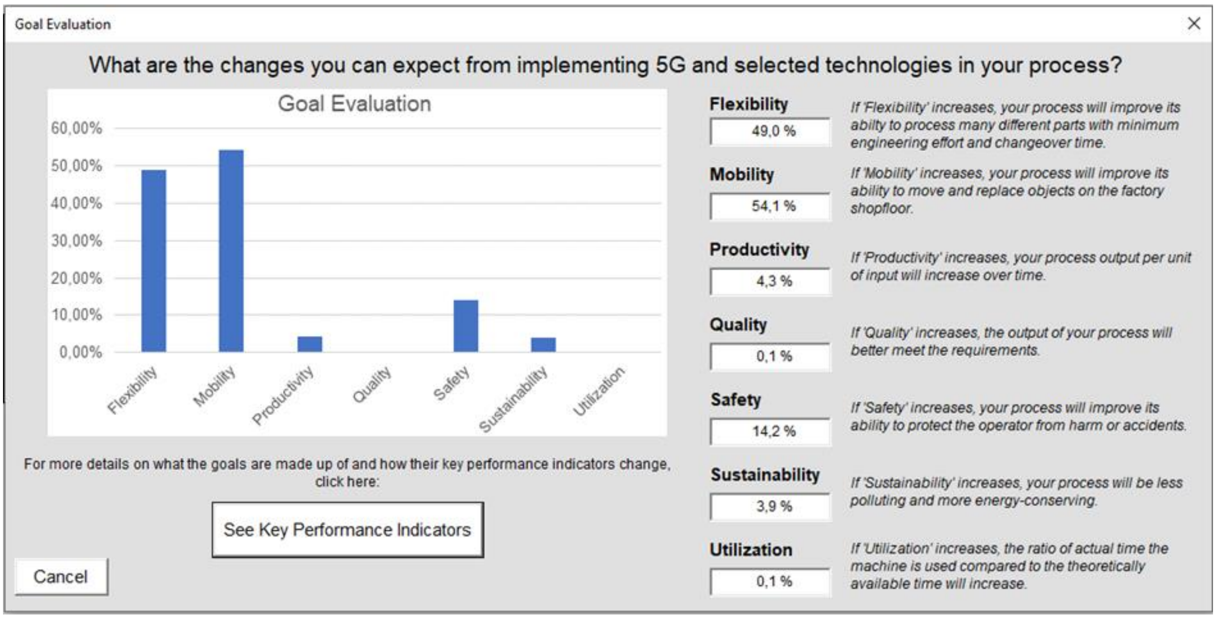

Figure 6.7 Evaluation of technical 5G potential

The user gets a more detailed view on technical potential of 5G when clicking on the button *'See Key Performance Indicators*'. Results of key performance indicators are illustrated in Figure 6.8 to Figure 6.10. Quantitative changes are displayed as bar chart. Left bar indicates status quo based on acquired set of data. Right bar indicates potential state of application when user implements 5G technology. In addition to bar chart, relative change between status quo and 5G application is expressed as a percentage.

Figure 6.8 Evaluation of flexibility, mobility, and productivity

Figure 6.9 Evaluation of quality, safety, and sustainability

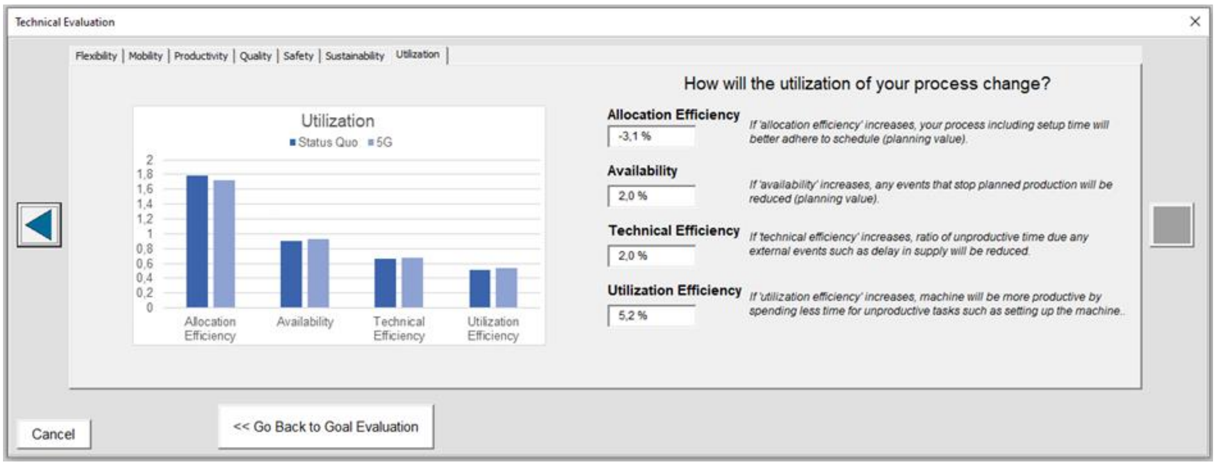

Figure 6.10 Evaluation of utilization

Before evaluating the economic potential of 5G the user is asked for further data regarding asset lifetime and interest rate (see Figure 6.11). For the investigated AGV application, the expected lifetime is determined to be 4 years and the applied interest rate is set to be 8% p.a. In a next step, the economic potential of 5G for the investigated AGV application is provided, see Figure 6.12.

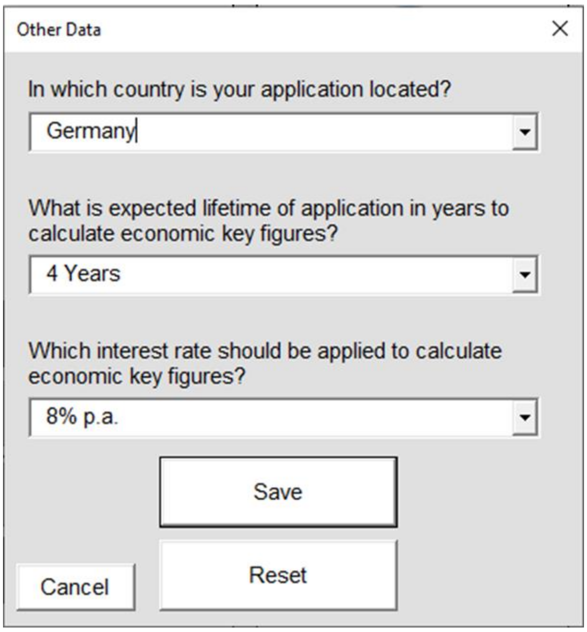

Figure 6.11 Assumptions for Economic Evaluation

In the figure it can be seen that, according to the information inserted into the tool, asset lifetime ends after 4 years. Net present value after four years is calculated to be about 400,000€ for application without 5G. When the user decides to implement 5G technology, NPV is determined to be about 1,000,000€. As a result, NPV can be more than doubled for specific application. This gives the production company an idea, how much they could spend for 5G technology in order to increase their revenues.

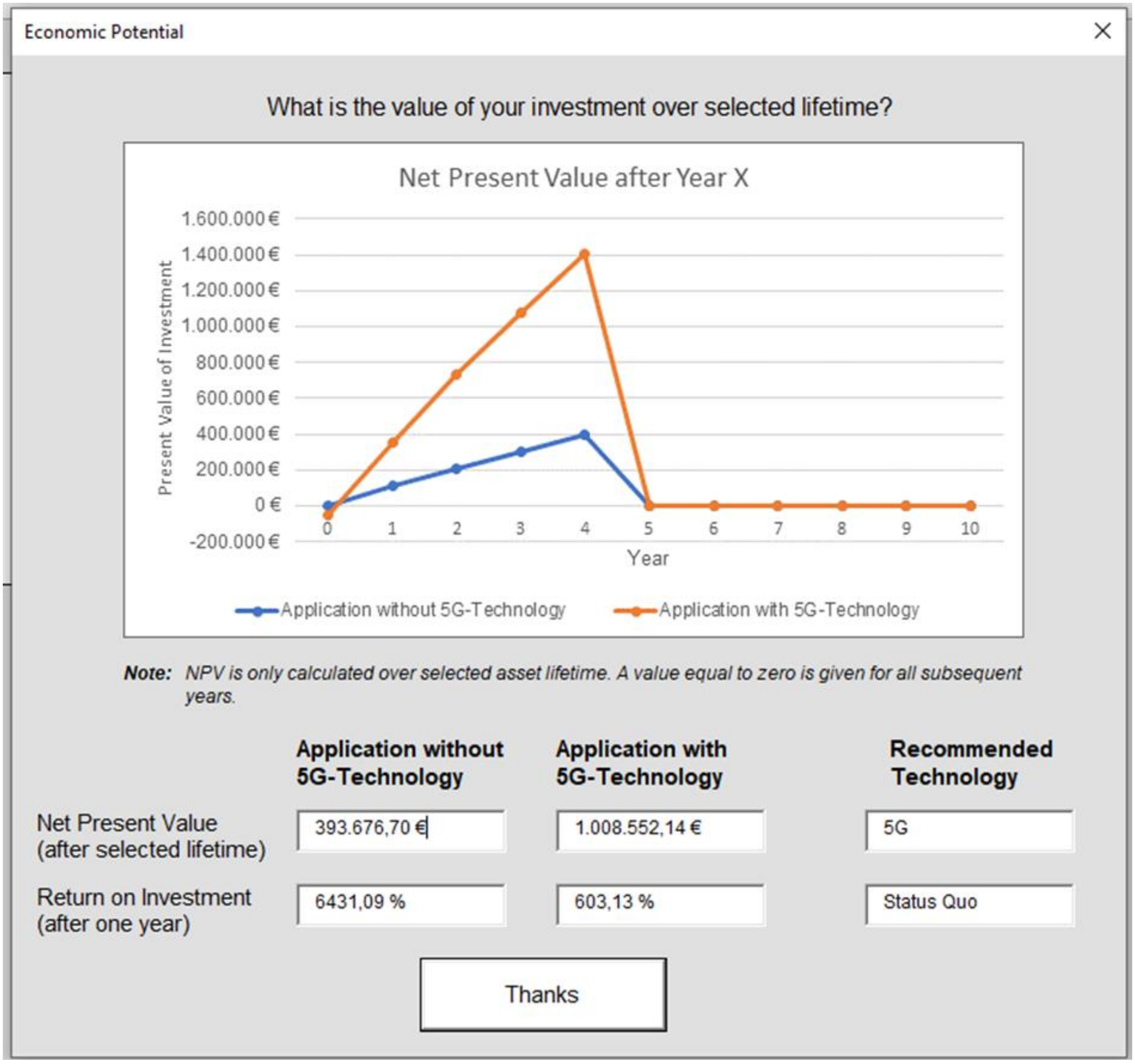

Figure 6.12 Evaluation of economic 5G potential

7 Conclusion and outlook

The goal of this deliverable was to quantify the business value of 5G implementation for industrial actors.

The developed evaluation model checks for the necessity of 5G technology based on morphologies that elaborate deficits of existing ICTs and the potential of the novel 5G technology. The evaluation model includes a set of technical and economic goals used to quantify the potential of 5G technology from both technical and economic perspectives. The goals are calculated by selected key performance indicators. Key performance indicators are measured by the selected set of data, which is categorized into product data, process data, failure data, and facility data. The set of data is used to characterize the behavior and performance of an application.

The impact of 5G technology on the behavior and performance of applications has been assessed based on literature. The manufacturing industry is expected to benefit from 5G regarding two main aspects. First, 5G provides low latency, high reliability, and high availability, and its wireless nature makes wired connections dispensable. Second, 5G facilitates measurement, analysis, and storage of high amount of data which paves the way for automatically controlled applications. Applications that are controlled in near real-time can benefit from advanced 5G-enabled technologies with short cycle times. 5G-enabled technologies involve condition-based monitoring to measure application behavior, artificial intelligence and machine learning models to manipulate application's behavior using smart algorithms, and edge computing to provide fast computing and high processing power to the application. The impact of 5G-enabled technologies on applications has been analyzed based on literature. Furthermore, the developed framework has been integrated into the Excel environment to build a user-friendly interface for both data acquisition and application evaluation. Finally, the model has been applied to an AGV application to demonstrate the working principle of the model.

In the following, possible adaptations and advancements of the framework are discussed.

- Effects are only quantified in case the literature provides reliable data. In the future, recording data of real applications both with and without 5G connectivity is highly recommended to verify the quantitative impact of 5G and to adjust the framework according to findings.
- The current framework is developed to evaluate a single application. This implies that interactions between several applications are neglected, and the user should be aware of this. Evaluating manufacturing islands, production lines, or even entire production shopfloor is conceivable in the future. One possible solution to implement several applications into the framework is the aggregation of single applications. The developed tool could accumulate input from every single application and perform the economic and technical evaluation based on aggregated data. Further research would then be necessary to evaluate technical interfaces between single applications, the potential benefit from network slicing, and possible economies of scale through common databases.
- It is assumed that applications require either full human involvement or no human involvement at all. Practice will show whether the assumption is justified or whether part-time human involvement is necessary to be integrated into the framework.
- Costs of implementing 5G-enabled technologies, namely condition-based monitoring, artificial intelligence, and machine learning models, and edge computing, are estimated. In

the future, market research should be carried out to verify implementation costs. Furthermore, different pricing models could be implemented into the future framework to find the most cost-efficient strategy for each user.

- The developed framework has been embedded into the software environment using Excel VBA. However, the Excel tool should be transferred to a more user-friendly python tool in the next step.

Regarding the economic evaluation, this report only covers the analysis of one use case. However, other use cases (e.g., BLISK production, human-machine interaction) will be considered within the project.

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Appendix

A1: List of abbreviations

Abbreviation	Explanation
A	Availability
ACCR	Accident ratio
ACR	Compressed air consumption ratio
AE	Allocation efficiency
AGV	Autonomous guided vehicle
AI	Artificial intelligence
BTU	British thermal unit
C2C	Control-to-control
CAPEX	Capital expenditure
CBM	Condition-based monitoring
CF	Cash flow
cm	Centimeter
CO_2	Carbon dioxide
CPU	Central processing unit
CSI	Channel state information
CW	Carbon weight
Dev.	Devices
E	Effectiveness

E2E	End-to-end
ECR	Electric power consumption ratio
ERP	Enterprise resource planning
EUR	Euro
FPY	First pass yield
GB	Gigabyte
GCR	Gas consumption ratio
GDP	Gross domestic product
i	Interest rate
ICT	Information and communication technology
IoT	Internet of things
IRR	Internal rate of return
IT	Information technology
KB	Kilobyte
kg	Kilogram
km/h	Kilometers per hour
KPI	Key performance indicator
kWh	Kilowatt-hour
m	Meter
m^2	Square meter
Max	Maximize
MB	Megabyte
Mbit/s	Megabit per second

Mbps	Megabit per second
MF	Machine flexibility
MHM	Material handling mobility
Min	Minimize
ML	Machine learning
mMTC	Massive machine type communication
MNO	Mobile network operator
ms	Millisecond
MTBF	Mean time between failures
MTTR	Mean time to repair
NPV	Net present value
OPEX	Operational expenditure
OTD	On-time delivery
p.a.	Per year
QoS	Quality of service
QR	Quality ratio
RFID	Radio frequency identification
RoI	Return on investment
RR	Rework ratio
s	Second
SP	Space productivity
SR	Scrap ratio
SUR	Setup ratio

t	Period of time
TE	Technical efficiency
TR	Throughput ratio
UE	Utilization efficiency
URLLC	Ultra-reliable low-latency communication
WCR	Water consumption ratio
WE	Worker efficiency

A2: Mathematical equations

Element		Mathematical Equation
$Actual\ application\ busy\ time$	=	$Actual\ application\ processing\ time + Application\ downtime$
$Actual\ application\ execution\ time$	=	$Actual\ application\ busy\ time + Transport\ time$
$Actual\ application\ processing\ time$	=	$Actual\ application\ setup\ time + Actual\ application\ production\ time$
$Actual\ application\ production\ time$	=	$Batch\ size \cdot Runtime\ per\ part$
$Actual\ personnel\ attendance\ time$	=	$Average\ number\ of\ shifts\ per\ day \cdot Personnel\ work\ time\ per\ shift$
$Actual\ personnel\ work\ time$	=	$Average\ number\ of\ shifts\ per\ day \cdot (Personnel\ work\ time\ per\ shift - Personnel\ break\ time\ per\ shift)$
$CAPEX_{Material,Setup}$	=	$(Number\ of\ wired\ sensors\ per\ application \cdot Cost\ of\ wired\ sensor) + (Number\ of\ wireless\ sensors\ per\ application \cdot Cost\ of\ wireless\ sensor) + (Number\ of\ control\ units\ per\ application \cdot cost\ of\ controller) + Cost\ of\ cables$
$CAPEX_{Process}$	=	$CAPEX_{Material,Setup}$
$(Failure\ events)_{Long-term}$	=	$(Failure\ events)_{Mechanic\ Failure} + (Failure\ events)_{Collision} + (Failure\ events)_{Wrong\ Task\ Execution} + (Failure\ events)_{Wrong\ Setup} + (Failure\ events)_{Cyber\ Attack}$
$(Failure\ events)_{Short-term}$	=	$(Failure\ events)_{Control\ System\ Malfunction} + (Failure\ events)_{Disabled\ Communication}$
$Fall\ off\ quantity$	=	$Produced\ quantity - Good\ quantity$
$Good\ quantity$	=	$(Produced\ quantity - Inspected\ quantity) + First\ time\ good\ quantity + Rework\ quantity$
$Number\ of\ accidents$	=	$Number\ of\ human\ caused\ accidents + Number\ of\ application\ caused\ accidents$
$Number\ of\ Failure\ Events$	=	$(Failure\ events)_{Short-term} + (Failure\ events)_{Long-term} + Number\ of\ failure\ events\ for\ unknown\ reasons$
$On\ time\ customer\ orders$	=	$Total\ number\ of\ customer\ orders - Number\ of\ delayed\ customer\ orders$
$OPEX_{Accidents}$	=	$Number\ of\ accidents \cdot (Average\ medical\ cost\ per\ accident + Average\ financial\ compensation\ cost\ per\ accident + Average\ cost\ for\ training\ new\ employee\ to\ operate\ the\ applicatio$
$OPEX_{Complaint}$	=	$Number\ of\ customer\ complaints \cdot Average\ cost\ for\ customer\ complaint$
$OPEX_{Consumption}$	=	$(Compressed\ air\ consumption \cdot Cost\ of\ compressed\ air) + (Gas\ consumption \cdot Cost\ of\ gas) + (Electric\ power\ consumption \cdot Cost\ of\ electric\ power) + (Water\ consumption \cdot Cost\ of\ water)$

$$OPEX_{Disposal} = Scrap\ quantity \cdot Disposal\ cost\ per\ part$$

$$OPEX_{Downtime} = Cost\ of\ planned\ application\ downtime \cdot Planned\ application\ downtime + Cost\ of\ unplanned\ application\ downtime \cdot Unplanned\ application\ downtime$$

$$OPEX_{Facility} = OPEX_{Shopfloor} + OPEX_{Consumption}$$

$$OPEX_{Failure} = OPEX_{Repair} + OPEX_{Accidents} + OPEX_{Penalty} + OPEX_{Complaint}$$

$$OPEX_{Material} = Produced\ quantity \cdot Material\ cost\ per\ part$$

$$OPEX_{Operation} = Actual\ personnel\ attendance\ time \cdot Hourly\ wage\ of\ application\ operator$$

$$OPEX_{Penalty} = Number\ of\ delayed\ customer\ orders \cdot Average\ penalty\ cost\ per\ delayed\ order$$

$$OPEX_{Personnel,Setup} = Actual\ application\ setup\ time\ \cdot Hourly\ wage\ of\ setup\ staff \cdot Number\ of\ setups$$

$$OPEX_{Process} = OPEX_{Downtime} + OPEX_{Personnel,Setup} + OPEX_{Operation}$$

$$OPEX_{Product} = OPEX_{Material} + OPEX_{Quality\ Control} + OPEX_{Rework} + OPEX_{Disposal}$$

$$OPEX_{Quality\ Control} = Inspected\ quantity \cdot Quality\ control\ cost\ per\ part$$

$$OPEX_{Repair} = Time\ to\ repair \cdot Hourly\ wage\ of\ repairment\ staff + Number\ of\ failure\ events \cdot Average\ material\ cost\ to\ repair\ application's\ failure$$

$$OPEX_{Rework} = Rework\ quantity \cdot Average\ Material\ Cost\ for\ Rework + Rework\ quantity\ \cdot Time\ to\ Rework \cdot Wage\ of\ Rework\ Staff$$

$$OPEX_{Shopfloor} = Total\ plant\ area \cdot Facility\ rental\ cost + Total\ plant\ area \cdot Facility\ maintenance\ cost$$

$$Other\ loss = Total\ production\ losses - Storage\ and\ transportation\ loss$$

$$Planned\ application\ busy\ time = Planned\ application\ processing\ time + Planned\ application\ downtime$$

$$Planned\ application\ execution\ time = Planned\ application\ busy\ time + Planned\ transport\ time$$

$$Planned\ application\ processing\ time = Planned\ application\ setup\ time + Planned\ application\ production\ time$$

$$Planned\ application\ production\ time = Batch\ size\ \cdot Planned\ runtime\ per\ part$$

$$Planned\ transport\ time = (Planned\ transport\ time)_{WarehouseToApplication} + (Planned\ transport\ time)_{ApplicationToStorageLocation}$$

$$Revenues_{Individualization} = Produced\ quantity \cdot Additional\ expected\ profit\ by\ individualization \cdot Percentage\ of\ individualized\ products$$

$$Revenues_{Product} = Revenues_{Sale} + Revenues_{Individualization}$$

$$Revenues_{Sale} = Good\ quantity \cdot Selling\ price\ per\ part$$

$$Scrap\ quantity = Inspected\ quantity - First\ time\ good\ quantity - Rework\ quantity$$

$$Spare\ area = Total\ plant\ area - Manufacturing\ area - Rework\ area - Storage\ area$$

$$Time\ to\ failure_{Long-term} = Time\ between\ failures - Time\ to\ repair_{Long}$$

$$Time\ to\ failure_{Short-term} = Time\ between\ failures - Time\ to\ repair_{Short-Term}$$

$$Time\ to\ repair = (Time\ to\ repair)_{Long-term} \cdot (Failure\ events)_{Long-term} + (Time\ to\ repair)_{Short-term} \cdot (Failure\ events)_{Short-term}$$

$$Total\ energy\ consumption = Compressed\ air\ consumption + Gas\ consumption \cdot Factor_{BTU \to kWh} + Electric\ power\ consumption$$

$$Total\ production\ losses = Fall\ off\ quantity - Scrap\ quantity$$

$$Transport\ time = (Transport\ time)_{WarehouseToApplication} + (Transport\ time)_{ApplicationToStorageLocation}$$

$$Unplanned\ application\ downtime = Application\ downtime - Planned\ application\ downtime$$