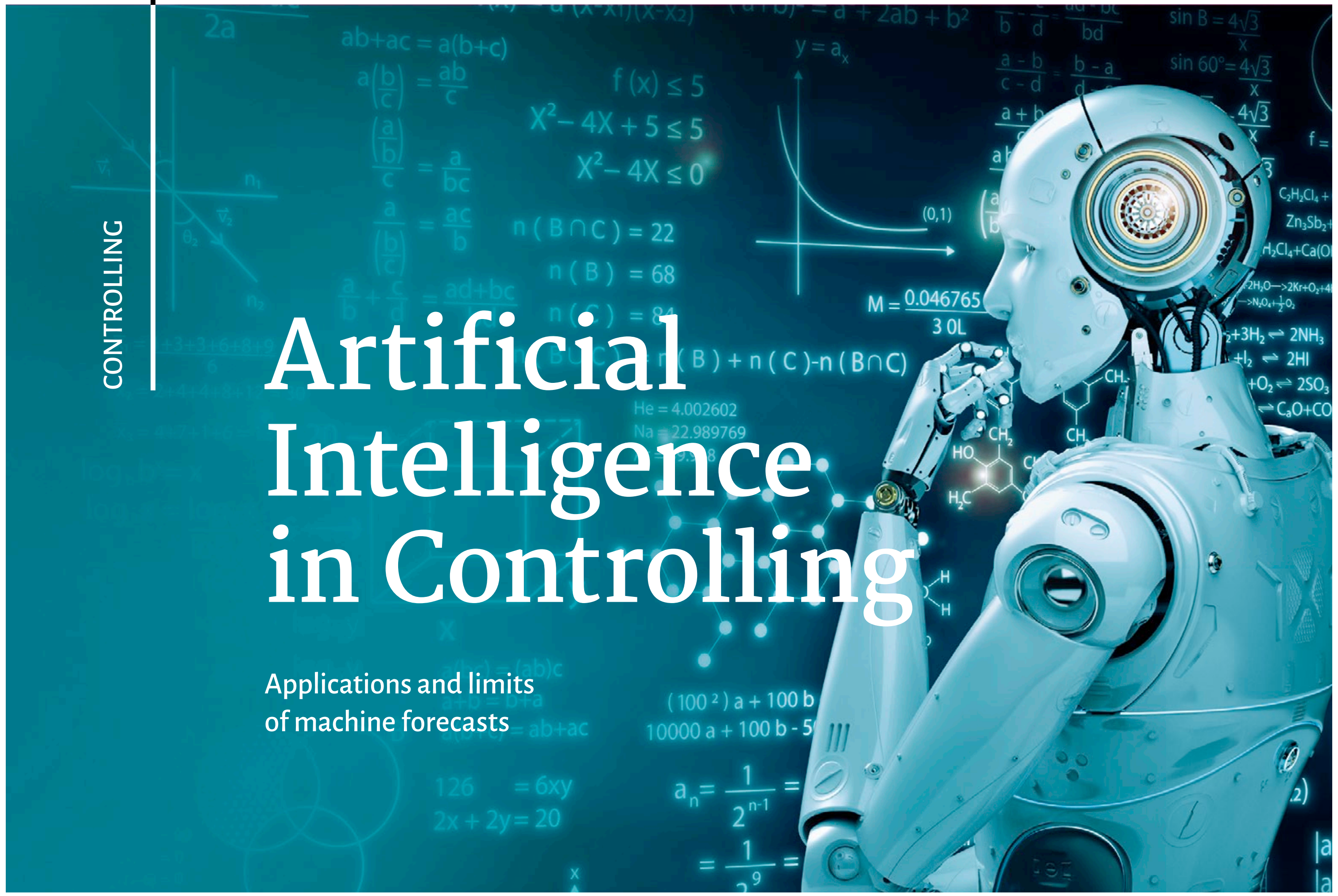
CONTROLLING



Artificial Intelligence in Controlling

Applications and limits of machine forecasts

International Association of Controllers

The effects of digitization can be felt in two very different fields of controlling. On the one hand in the automation of repetitive routine tasks (Robotic Process Automation) and on the other hand in the support or automation of challenging, analytical tasks (machine forecasts, AI). While the automation of routine tasks has been proceeding quite well, especially in large companies, the support of analytical tasks seems much more difficult. According to a study of the German Federal Ministry of Economics, only 5% of German companies use AI in one of their business units.[1] The amount of companies that use AI in controlling is thus vanishingly small. At the same time there are high expectations for AI-systems in controlling.[2] This article was written before the start of the corona crisis. It illuminates both the limits of the prognostic ability, and the possible applications, of machine forecasts.

A Paradigm Shift in the Area of Planning, Budgeting and Forecasting?

Lamenting an uncertain environment that is hard to predict, the premature obsolescence of plans and budget policy "games" has a long history. The Beyond Budgeting Round Table (BBRT) made loud demands for the end of classical planning in the early 2000s. In the wake of the 2008 financial crisis the term VUCA – Volatility, Uncertainty, Complexity and Ambiguity - established itself as synonymous with the difficulty of predicting future developments. As an answer to this "new normal", concepts like Modern Budgeting, Scenario Planning, Fluctuation Margin Planning or Rolling Forecasts have been introduced, which propagated the departure from detailed, pinpoint planning and prognoses in various ways.

But with the advent of the digitization a new paradigm shift seems to have started. The access to new data sources (Big Data), nearly unlimited processing power and AI-systems have quickly led to buzz words like Predictive Analytics and the first applications of AI-based machine forecasts. Through this, the faith in the predictability of the future has been resurrected – at least until the start of the corona crisis. The few reports of experiences, primarily from large companies, seem to confirm the feasibility of making predictions via AI and the superiority of machine forecasts. Figure 1 shows the monthly development of human and machine year-end forecasts of a large international company. Here the machine forecast has indicated the downturn three months earlier than the controller, and also predicted the end-of-year result a little more precisely.

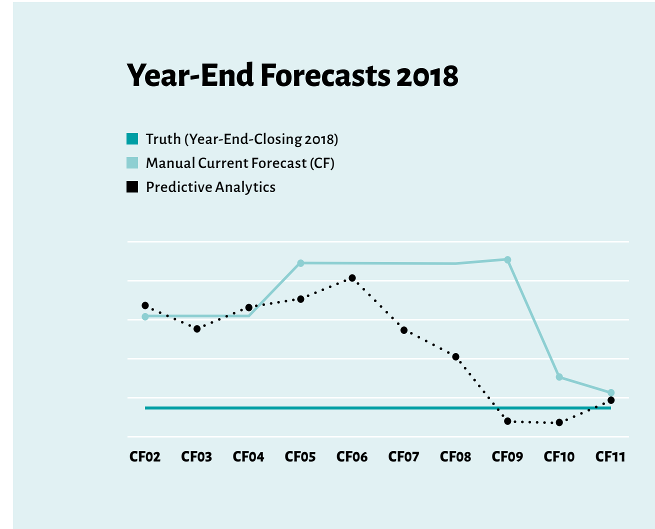


Fig. 1: Machine vs. human year-end forecast (real-life example)

The differences between human and machine forecast can be plausibly explained by the complementarity of human and machine information processing. However, realistic expectations regarding the predictive accuracy of machine planning and forecasts are in order, despite the positive experiences, because there are limits to the ascertainability and planning capacity of AI in a VUCA-context as well. Even the machine forecast in the "successful example" of figure 1 was considerably too optimistic until August. These limits will be discussed from the perspective of complexity and cybernetics.

The Limits of Predictability due to Complexity and Cybernetics

Dealing with complexity is nowadays regarded as one of the biggest challenges in management. Managers have to consider an ever-increasing number of factors in corporate management, that also change at an increasingly rapid pace and are highly interconnected. Key drivers of this development are globalization and paradoxically the rapid progress of digitization, that connects the world in real-time and increases its speed of change. The handling of complexity has been studied by cyberneticists in particular. Pioneers like Ashby, Beer, Forrester, Luhmann, Ulrich, Probst, Gomez, Malik, Dörner or Vester have already laid the groundwork for this a long time ago, which, considering the limits of artificial intelligence, is now more current than ever. Here Bremermann's limit and the partial ascertainability and controllability of complex systems have been selected as examples.

Bremermann's Limit

According to Bremermann's limit there is an insurmountable, absolute limit to human knowledge, which cannot be overcome, no matter how great the advancements in digitization are. Due to the atomic structure of matter there is an upper limit to information processing, which cannot be surpassed by any computer or brain made of matter: no system consisting of matter can process more than $2^{*}10^{47}$ bits per gram and second, corresponding to the speed of light and the Plank constant.[4] As a consequence not even the strongest cloud-based computer clusters, like i.e. Hadoop, have enough processing power to make exact forecasts in today's complex, competitive environment. Malik made an interesting comparison in his habilitation thesis, in which he calculates the theoretical limit of the information processing capacity based on the assumption that the entire earth's mass since the start of the history of the earth was a giant computer, that was permanently processing information. He then compares this information processing capacity to the complexity of typical management decision-making situations and thereby shows the limited forecasting ability.[5]

Partial Ascertainability and Controllability of Complex Systems

Figure 2 shows the structure of complex systems like that of our modern economic system. They consist of a multitude of elements [6] (a to h) and relations (arrows between the elements), while the system is split into one part that is visible (a, b, d, e, g, h) to the actor A (manager, controller) and one part that is invisible (c, f). An example for an invisible element would be the corona virus before its outbreak. This has an important consequence: we do not know that certain elements exist and cannot factor them into our decisions. Thus, the system is only partially ascertainable and therefore it can also only partially be modelled via AI-systems.

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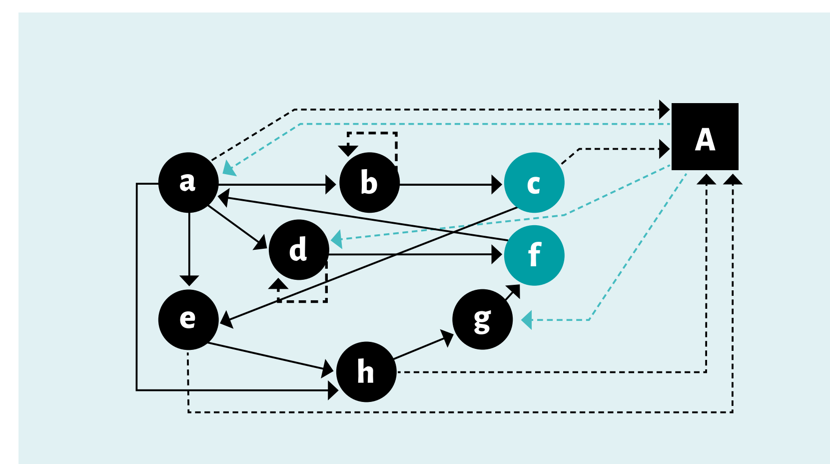
Fig. 2: Structure of complex systems [7]



Complex systems can be further divided into active elements (b, d) that can change independently, and passive elements (a, c, e, f, h, g). Complex systems have their own momentum through these active elements. They do not wait for the interventions of the actor, but rather change themselves. Both the elements themselves and the relationships between the elements can change without an outside influence. Consequently, the input (interventions from management) is not the only thing that determines the output now. In truth the output depends on the input and on the states of the system. That is why their behavior constantly surprises us. Forrester called them counterintuitive because known phenomena suddenly behave differently than we would expect from experience. [8] This also applies to machine forecasts based on artificial intelligence, which ultimately should make accurate predictions for the future based on historical data (states of the system). The momentum of complex systems, while taking Bremermann's limit into consideration, has profound consequences: the ideal of exact forecasts becomes impossible. Ultimately, we must make do with patterns.

Finally, managers in complex systems only have limited management options. To achieve objectives, the actor must change the state of certain elements. The elements of the system are broken into elements that can be influenced directly (dashed line from the actor to the elements a, d, g), elements that can be influenced indirectly (b, e, h), and elements that cannot be influenced (c, f). In addition, the elements can hardly be influenced in isolation, because they are highly interconnected and the actor is influenced by the elements in turn (dashed lines from the elements a, e, h to the actor). Thus, not only the forecasting ability is limited, but the controllability as well.

In summary, it can be deduced from these two fields, that, from a cybernetic and a system-theoretical perspective, the ideal of exact forecasts will remain an unattainable ideal even in the age of AI and machine forecasts. This should not mean, however, that machine forecasts could not lead to improvements in controlling. On the one hand the same result can be achieved with lower expenses through automation, on the other hand, through the complementarity of human and machine information processing, improvements in quality can be achieved.

The Complementarity of Human and Machine Information Processing

The question why machine forecasts could be superior to human ones, can largely be answered from the perspective of shortcomings of human rationality. The achievements, or rather the limitations, of the human brain can be summarized as follows:[9]

- People can only use the information they have learned or that is quickly available externally (e.g. on paper). The human brain shows weaknesses in the retrieval of information.
- The human scope for solving problems is fairly small. Only a few pieces of information can be processed at the same time. No more than 5-9 informational or sensory units, so-called 'chunks', can be processed simultaneously in short-term memory.[10]
- The brain gets tired and can only continuously solve problems for a limited time. Constant thinking over a longer period is accompanied by an increasing frequency of errors.
- The brain works relatively slow. The speed, however, depends on the shape and familiarity of the problem type: lighting-quick human pattern recognition whether an apple is fresh or rotten vs. the sluggishness when doing mental arithmetic.

Beside those capacitive "skill-deficiencies", there are also behavioral shortcomings. For example, people are content with reaching their individual level of ambition and not necessarily the achievable maximum, or they make decisions for their personal gain and not for the benefit of the company. The cognitive limits and behaviors have been covered at length in literature. The long list of identified biases is proof of that. The following examples show typical human shortcomings in the creation of forecasts:

- Overconfidence frequently leads to optimistic prognoses
- People subconsciously adjust their prognoses to an "anchor" or point of reference. In the case of a forecast this can, for example, be the figures from the budget or from the previous year
- The receptiveness to new information increases if they support the intents of the decision-maker
- Power-based distortion of information, like the loss of prestige, leads to prognoses being upheld, even when the opposite case is already becoming apparent.
- Distance bias – because distant problems seem less important than immediate one, negative developments are not communicated right away

The examples given show, that the forecasting quality can be enhanced through the use of machine forecasts. On the one hand a greater amount of information can be included in the forecast, on the other hand machine forecasts are not subject to interest-based distortions ("emotionless forecast"). But you should be careful with this. An essential principle of artificial intelligence is the ability to learn and to improve itself. Optimization algorithms can determine the accuracy of the model and adapt it to heighten its future accuracy. Even though AI-systems do not have self-interests, human biases can be learned unintentionally through the data made available to the system. Besides the limitations of the human brain, one of its major strengths is worth mentioning too. The human brain regularly solves problems that were not posed as well. The brain does not have a static structure, on the contrary it is reorganized constantly. That is why problems are spontaneously seen in a new way. This characterizes the creativity and innovative capability of humans and is a major difference to machines.

Human-Machine Applications and Division of Tasks

The discussion so far has shown that

- AI-systems, or rather machine forecasts, are still not very widespread and in their infancy, but they are of great importance and hold great future potential.
- The ideal of exact prognoses will remain an unattainable one, even in the age of artificial intelligence, their use, however, can enhance human predictive power and automate or support the creation process.
- People do, in fact, have cognitive abilities that machines do not have (yet).

The question therefore is, how machine forecasts can be used best. Should they replace or supplement human forecasts? A distinction might be made between different support levels of "Assisted Intelligence, Augmented Intelligence, Autonomous Intelligence", similar to the way it is done in autonomous driving.[11] In the case of Assisted Intelligence, the entire forecast process remains in the hands of the controller. The AI or the machine forecast does support work, following the specific requirements of the controller. The controller then decides the result of the forecast. For Augmented Intelligence, the forecast of the controller and the machine forecast are created in parallel. The differences are analyzed and the controller or the manager decides which result will be used. An example for using Augmented Intelligence in the forecast process is the SAP AG. If the discrepancy between the forecasts exceeds a certain threshold value, the concerned departments must explain why they think that they are right, not the system. In the last stage of Autonomous Intelligence, the machine forecasts replace the human forecasts; controllers and managers rely on the AI-system. Alongside the support level, the question of the requirement level for the AI must also be considered. In analogy to the stages of development of analytics, the expectations for the AI-system might only be the provision of relevant information on variances, as a basis for the actual prognosis (descriptive, diagnostic). But in most cases companies are not content with that and implement a quantitative forecast (predictive). The highest requirement level is set for an AI-system, that not only predicts the likely result, but also the measures necessary to attain it (prescriptive). But that still seems like a vision of the future from today's point of view. ■

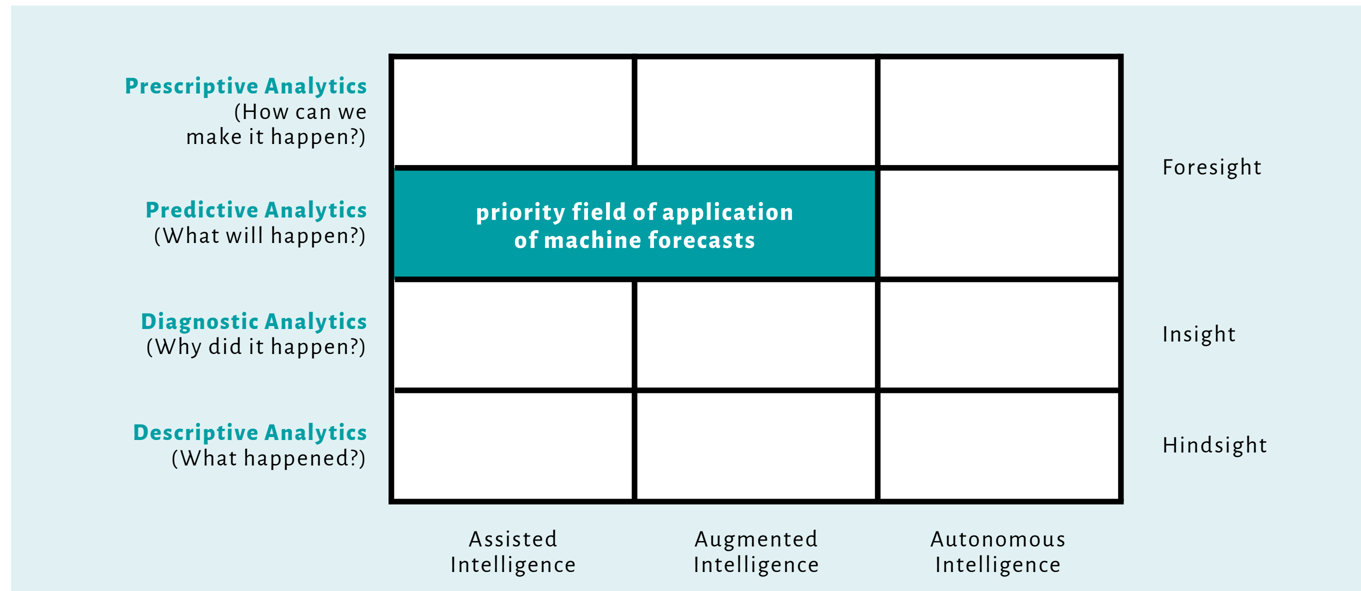


Fig.3: Applications and support levels of machine forecasts

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