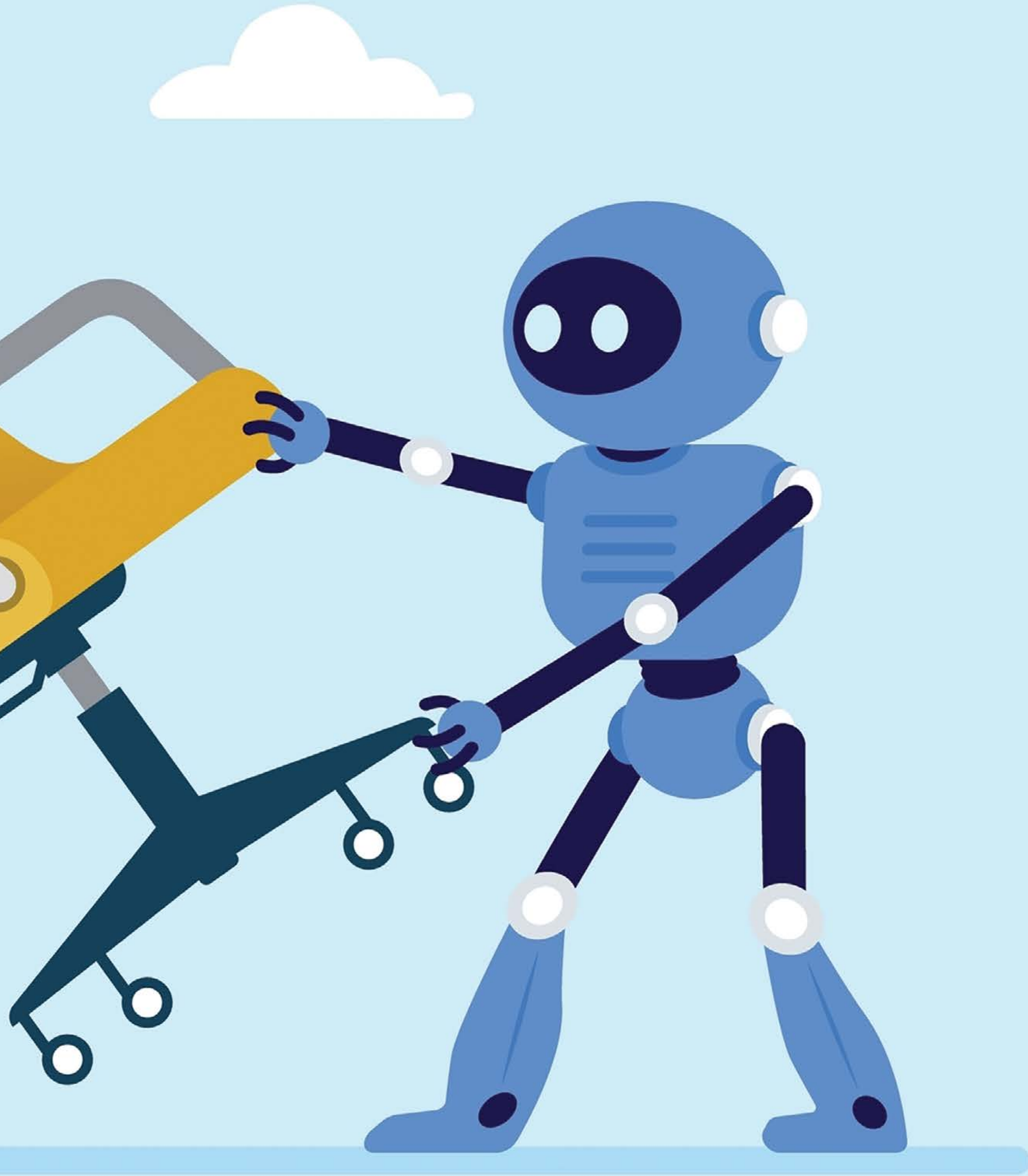
Digitalisation: So what?

Why AI will increase the need for experts

Mladen Banovic



ABSTRACT

Digitalisation is transforming transformer monitoring, enabling earlier detection of potential issues and generating more data than ever before. However, improved visibility does not automatically lead to better decisions. This article examines the gap between data and action, the limitations of digital models and twins, and the evolving role of AI as a support tool rather than a replacement for expert judgment.

As systems detect more complex and earlier-stage conditions, decision-making shifts toward deeper interpretation under uncertainty. The article argues that digitalisation increases the need for expertise and highlights the importance of trust and operational frameworks in making data actionable.

KEYWORDS:

digitalisation, monitoring, diagnostics, digital twins, predictive maintenance

More data does not lead to better decisions without a clear structure for making them

Introduction

Digitalisation has become one of the dominant forces shaping the transformer industry. Monitoring systems are expanding, continuous data acquisition is scaling across fleets, and analytical tools are evolving from traditional threshold-based methods toward more advanced approaches, including AI-based techniques. The expectation is clear: more data should lead to better decisions. In practice, it often does not. This gap is not new; it has accompanied the evolution of monitoring and diagnostics from its earliest digital forms.

Across utilities, manufacturers, and service providers, the industry is generating more information about transformer condition than ever before. Dissolved gas analysis, partial discharge monitoring, fibre-optic temperature measurement, moisture tracking, and a growing range of online sensors provide continuous visibility into transformer behaviour. Digital platforms aggregate these signals, while a growing range of analytical models attempt to translate them into actionable diagnostics; a task that has consistently proven more difficult in practice than in concept.

Despite this progress, a fundamental question remains unresolved: **Why does better data still not consistently translate into better decisions?**

The answer does not lie in the absence of technology, but in the structure surrounding it.

Decision-making as the primary constraint

The industry has largely solved the problem of measurement. Modern monitoring systems are capable of detecting anomalies at earlier stages of fault development. Digital platforms can process large datasets and identify patterns that would be impossible to detect manually.

However, the presence of data does not automatically define action.

In many organisations, monitoring systems generate alarms, but the response to those alarms remains unclear. Responsibilities are not always defined, escalation paths are inconsistent, and decisions are often deferred or left to individual judgment rather than structured processes. This is not a new limitation, but a persistent one that has accompanied the adoption of monitoring systems across multiple generations. An expectation is that artificial intelligence can fill this gap.

Some utilities are beginning to explore AI-based systems not only to analyse data, but to interpret it and, in some cases, to replace the role of human experts. This approach is understandable given the shortage of experienced personnel and the increasing volume of data. It is also a pattern the industry has seen before with each new generation of analytical tools. However, alternative approaches, focused on supporting rather than replacing expert judgment, are more likely to succeed in practice.

The vast majority of monitoring data does not indicate a problem. It represents normal operating conditions. The challenge is not to analyse everything in detail, but to reliably identify when something deviates from expected behaviour.

AI is ideally suited for this task. It can process large volumes of data, identify anomalies, and prioritise events that require attention. What it should not do is make final decisions.

The correct model is therefore not AI instead of experts, but AI in support of experts.

AI scales data, while experts carry the responsibility for judgment.

Gap in operational decisions

The concept of continuous monitoring is no longer new. The limitations of periodic testing have been recognised for decades. Failures can develop between test intervals, and offline measurements provide only snapshots of a continuously evolving system. This has been well understood for a long time.

The industry has responded accordingly. Online monitoring systems are now widely deployed, providing real-time data on transformer condition. In many cases, the technical capability to observe asset behaviour continuously is already in place.

What has not evolved at the same pace is the operating model for decision-making.

Continuous data requires continuous interpretation, continuous evaluation, and, ultimately, timely decision-making. This demands clearly defined thresholds for action, structured escalation processes, and an organisational readiness to respond in real time.

In practice, these elements are often missing. The result is a structural mismatch: continuous monitoring feeding into discontinuous decision processes.

The industry has accepted continuous monitoring, but **it has not yet developed meaningful operational decision-making.**

Interpretation challenge

Another recurring assumption is that adding more sensors will improve insight. While this is true in principle, it does not hold automatically in practice.

Each monitoring technique provides a partial view of transformer condition. Dissolved gas analysis reflects chemical processes, partial discharge monitoring captures electrical activity, temperature measurements indicate thermal stress, and moisture monitoring relates to insulation ageing. None of these signals, in isolation, provides a complete picture of the underlying condition.

When multiple monitoring systems are deployed independently, the result is not clarity, but complexity. Different signals may point to different conclusions, and without integration, the number of potential interpretations increases rather than decreases.

This is why multi-modal sensing and data fusion are essential. The objective is not simply to collect more data, but to correlate signals and build a coherent, physically meaningful interpretation.

Without this integration, more data does not reduce uncertainty. **It can even amplify it.**

A further step in this direction is emerging with the development of large language models and advanced data integration frameworks. These systems are expected to go beyond the analysis of online monitoring data and incorporate additional sources of information, including periodic test results, environmental conditions, and even forecast data.

This creates the potential for a more holistic understanding of transformer behaviour, where condition assessment is no longer based on isolated signals, but on a broader operational context.

At the same time, this increased capability reinforces the central challenge.

AI will not replace experts; it will determine when their judgment is needed

As models integrate more variables and more complex relationships, their outputs become more difficult to interpret and validate. The need for structured data, transparent modelling assumptions, and expert oversight becomes critical.

Model assumptions

Most digitalisation efforts in the transformer industry rely on models. These models range from simple threshold-based rules to advanced physics-based simulations, AI-driven diagnostics, and digital twins. They are essential tools for interpreting data, simulating behaviour, and supporting decision-making.

However, they share a common limitation that is rarely addressed explicitly.

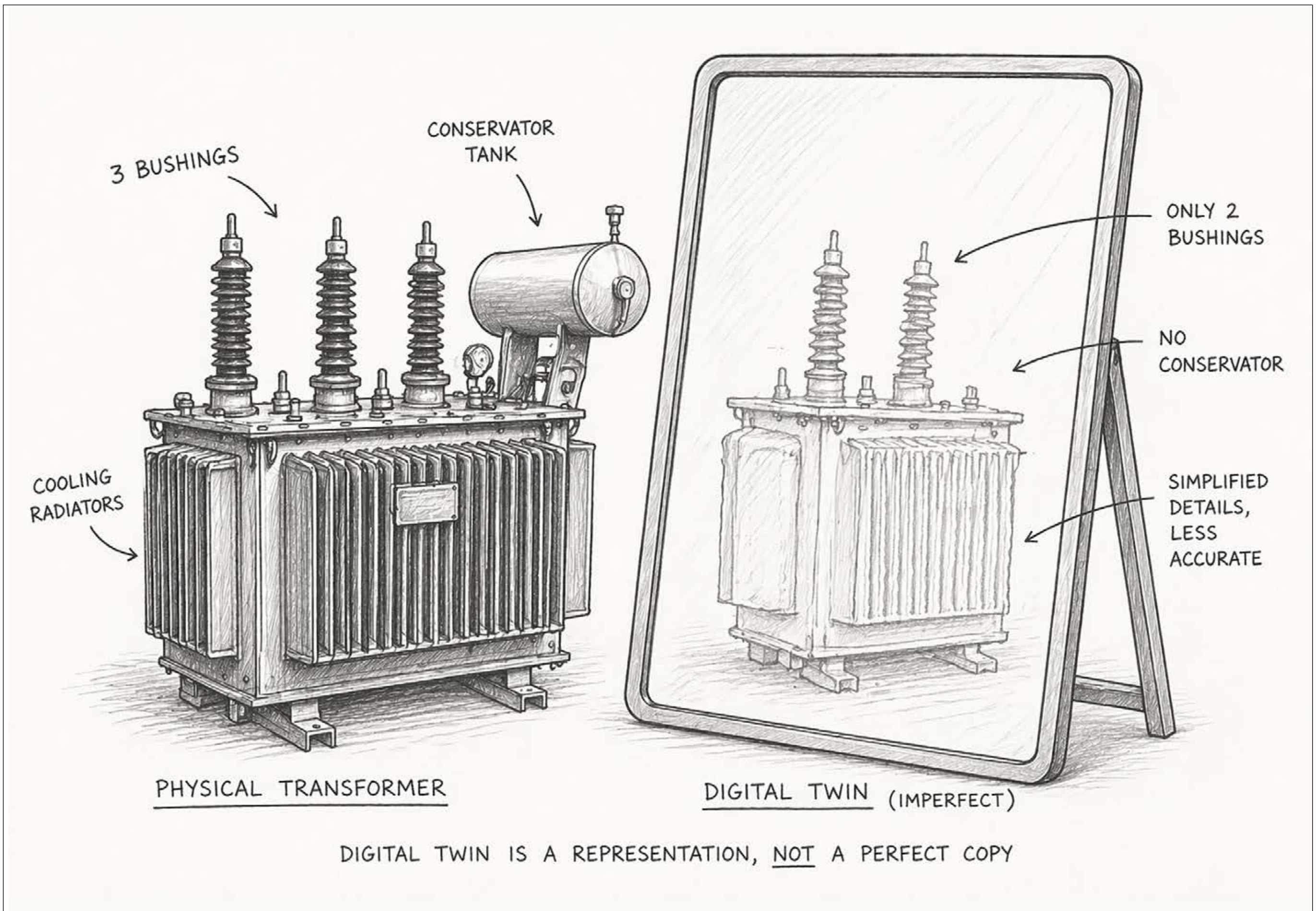
Most models still assume some form of equilibrium.

Moisture models assume equilibrium in moisture migration between oil and paper. Thermal models assume stable heat transfer conditions. Many diagnostic interpretations also rely on steady-state assumptions about gas generation or electrical stress.

In reality, transformers operate in a continuously changing environment.

Load varies. Ambient conditions fluctuate. Internal processes evolve dynamically. Moisture migrates, temperatures shift, and electrical stresses change over time. The system is rarely, if ever, in true equilibrium.

This has profound implications.



Transformers do not operate in steady state, yet most digital models still assume they do

If models assume equilibrium while the actual system is in transition, their outputs may be directionally correct but quantitatively inaccurate, often without this being immediately apparent. This affects not only the precision of diagnostics, but also the level of trust that operators can place in digital tools.

Digital twins, in particular, are often presented as accurate representations of transformer behaviour. In practice, their accuracy depends heavily on the validity of their underlying assumptions and their ability to capture dynamic, non-equilibrium conditions.

Transformers do not operate in steady state. **Yet most digital models assume they do.**

This gap is one of the most important, and least discussed, limitations of current digitalisation efforts.

Evolving role of expertise in the age of AI

The increasing use of AI in transformer diagnostics is often accompanied by concerns about the future role of human experts. In reality, the opposite trend is more likely.

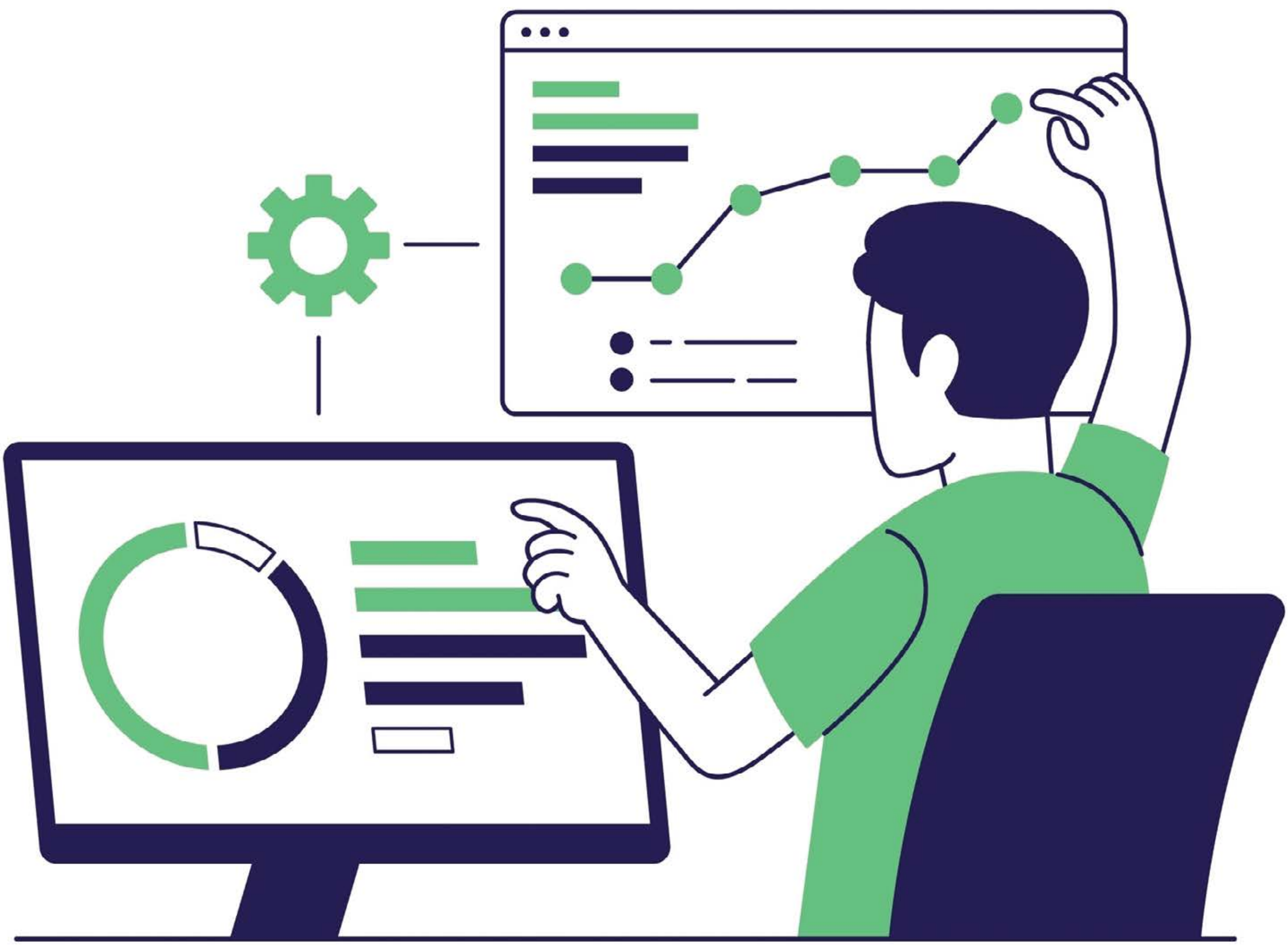
As monitoring systems become more sensitive and analytical tools become more advanced, the number of detected anomalies will increase. The role of AI will be to identify patterns, flag deviations, and generate insights at earlier stages, even before their significance is fully clear. Each of these alerts represents a potential issue that requires interpretation and judgment.

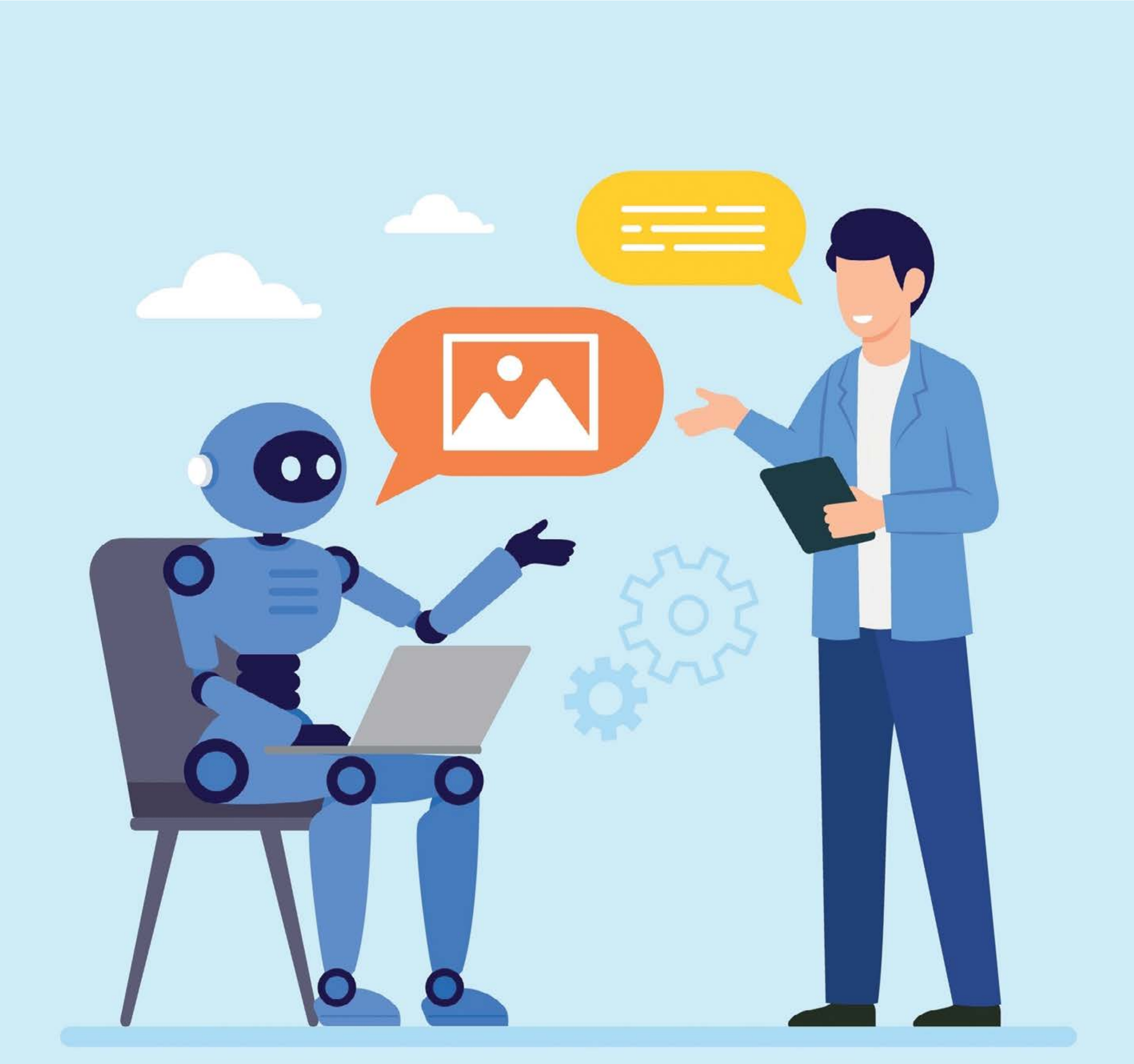
Instead of reducing the need for expertise, AI will most likely expand the scope of situations that require expert evaluation, shifting the role of experts from routine monitoring to complex and non-standard cases. This has two important consequences.

First, expert time becomes more valuable. By filtering out normal operating conditions, AI allows experts to focus on the cases where their knowledge is most needed.

Second, the demand for expertise increases. As more potential issues are identified at earlier stages, more decisions must be made, and more situations require informed judgement.

Experts who view AI as a threat are likely to be surprised by how AI amplifies their importance.





Shifting priorities

The context in which transformers operate is also changing.

Lead times for new transformers have increased significantly, in some cases reaching several years. At the same time, demand for electrical infrastructure continues to grow, driven by electrification, renewable integration, and the rapid expansion of data centres.

In this environment, the failure of a transformer is no longer just a technical event. It is a strategic risk. Replacing a failed unit may not be possible within an acceptable timeframe. The loss of a critical asset can directly affect system stability, project timelines, and financial performance.

Decision responsibility cannot be digitalised, even when data and analysis can

As a result, the objective of digitalisation is shifting. It is no longer primarily about improving efficiency or optimising performance. It is increasingly about **protecting the existing fleet.**

Monitoring, diagnostics, and predictive tools are essential not because they offer marginal gains, but because they help avoid irreversible losses.

Trust as the central requirement

It would be incorrect to conclude that the industry does not need more data. In many cases, additional measurements and improved visibility are still required. However, the priority is shifting.

The real challenge is not the absence of data, but the ability to trust it and use it effectively in decision-making. This

The more powerful our digital tools become, the more valuable expert judgment becomes

requires structured data models, consistent interpretation methods, and clear operational frameworks.

Tools that provide diagnosis together with probability, indicate uncertainty, and are trained on validated expert cases represent an important step in this direction. They reflect the reality that transformer diagnostics is not a deterministic process, but one that involves varying levels of confidence.

At the same time, organisational models must evolve to support these tools. Access to expertise, whether internal or external, must be facilitated. Communication between technical specialists and asset managers must improve, and decision processes must become more transparent and consistent to be effective in practice.

The industry does need more data. But it needs **trust and usable operational models even more.**

A shift in perspective

The transformer industry has made significant progress in digitalisation. Measurement capabilities have expanded, analytical tools have improved, and the potential for data-driven decision-making has increased.

At the same time, a new reality is emerging: digitalisation does not automatically lead to better decisions. Without clear decision architecture, integrated signals, validated models, and sufficient expertise, additional data can increase complexity rather than reduce it.

The next phase of digitalisation will therefore not be defined by new sensors or more advanced algorithms alone. It will be defined by how effectively the industry connects data to decisions. And perhaps most importantly, it will be defined by how it redefines the role of expertise in a world where information is no longer scarce.

Delegating complex decisions to algorithms is a risk

Final reflection

There is a common expectation that automation reduces the need for human involvement. In the case of transformer digitalisation, the opposite is likely to be true.

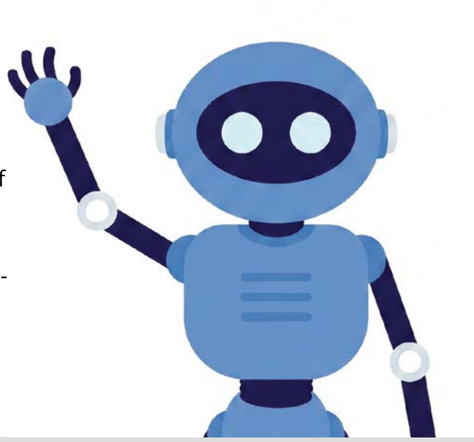
As monitoring and analytical systems become more capable, they will detect potential problems significantly earlier than was possible in the past. They will also begin to identify fault mechanisms that were previously not visible through online monitoring.

This does not necessarily mean that the number of cases requiring expert attention will increase. However, the nature of these cases will change. The issues identified will occur earlier, be less obvious, and often more complex, requiring deeper interpretation and higher levels of expertise to reach reliable conclusions.

The expected outcome is not more alarms, but better prevention by avoiding failures that would previously have developed unnoticed into catastrophic events. The ability to distinguish meaningful signals from false alarms, to understand the limitations of models, and to make informed decisions under uncertainty will become even more critical.

The idea that this complexity can be fully delegated to algorithms is a risk. As systems become more capable, expertise is not being replaced but becomes more important.

Digitalisation, in its current form, is not the end of expert judgment. It is the beginning of a new phase in which that judgment becomes the central element of reliable asset management, because more data does not lead to better decisions by itself. Better decisions come from how that data is understood, challenged, and owned.



Author

Mladen Banovic is a scientist and innovator in the field of energy transmission with 25 years of technical and managerial experience.

He currently holds the positions of Director and Editor-in-Chief at Merit Media Int. – the company behind the Transformer Magazine, Transformer Academy, Industry Navigator, and Transformer Forum brands.

During his career, he managed development of products and systems for worldwide use in electric power grids up to 1200 kV (currently the highest level in the world), the development and deployment of systems for smart grid and automated design, testing, diagnostic and monitoring systems.

Education: PhD, MSc, and BSc degrees in electrical engineering from the University of Zagreb, Croatia.

Affiliations: IEEE Senior Member, CIGRE, European Association of Science Editors (EASE), etc.