Beneficial Role of Humans and AI in a Machine Learning Age of the Telco EcoSystem

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Abstract

The adoption of new technology in the telecommunications industry raises challenges, particularly when exploiting advances in artificial intelligence (AI) (e.g. dynamic optimisation and machine learning). Indeed, opinions have been expressed that AI will either replace everyone, gain sentience or not be able to contribute to anything meaningful where human creativity and innovation are required. Nonetheless, the need to exploit recent advances in AI in a dynamic telecommunications ecosystem of Internet of Things (IoT), 5G and rapidly diminishing margins should be unquestionable. In a recent panel of automation in Software Defined Networks (SDN) and Network Function Virtualisation (NFV), the CTO of a large European Operator cited the most significant problem to solve was not the use of AI in automation but rather its introduction alongside human operators. However, recent research in the area of interactive optimisation and machine learning at the University of the West of England, Bristol, UK, has incorporated humans "in-the-loop" with AI and found that superior solutions can be achieved by humans and AI working together rather than separately. To examine these issues, we present relevant case studies from BT Research Laboratories and Aria Networks / Facebook. We analyse the case study evidence and recent advances in AI research to carefully discern the crucial causative factors that underpin the situation. Based on the analysis, we conclude that the case for engineers working collaboratively "in-the-loop" with AI is compelling, and will be of great benefit to telecommunications businesses and the people involved in the areas of process automation and dynamic optimisation.

1 Introduction

Artificial Intelligence (AI) is becoming ubiquitous. In the fields of telecommunications software defined network route planning, artificially intelligent algorithms inspired by biological metaphors are being increasingly applied in an attempt to optimise network topologies and configuration. Examples of such algorithms include evolutionary computing [1] and ant colony optimisation [2] among others. Such algorithms are useful because the increasing scale and complexity of telecommunications network planning results in

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a combinatorial explosion that exceeds human understanding and exact computational techniques such as exhaustive (brute-force) evaluation too. Other examples of artificially intelligent algorithms include artificial neural networks [3] for machine learning i.e. the derivation of meaning from data by classifying sets of data into various categories. Because of their ability to address network route planning optimisation at scale, artificially intelligent algorithms offer great potential for the optimisation and exploitation of advances in software defined networks (SDN) and Network Function Virtualisation (NFV).

However, as the application of AI to problems of increasing scale and complexity in the telecommunications ecosystem has widened, a number of concerns and possible misconceptions have emerged. These relate to:

- *a perception of AI bringing little or no benefit to network engineering.* The history of AI has previously shown a mixed picture of success. Over past decades, despite some significant advances, many early artificially intelligent algorithms have been found to be highly specific to particular 'toy' problems (i.e. they were not general), and struggle in the face of the scale and complexities of the realities of industrial problems, including those from the telecommunications domain. However, with the recent advent of increased processing power and the ready availability of vast quantities of data, AI has been more widely applied and shows increasing potential for network engineering.

- *a concern that automation will replace the engineer and jobs will be lost.* The business benefit of AI most often identified first is cost saving, with the implication that this means the replacement of people by machines. There may exist amongst a company's activities, areas where the combination of a sufficiently closed problem and a sufficiently low likelihood of major change mean that an activity can be run by (self-learning) algorithms without human intervention. However, these conditions imply market stability and independence of the particular activity from others. In other areas the rate of change is greater and managing a process entails finding an optimum amongst a large number of combinations of individually regular activities. This pertains in a telecommunications network, where standardised functions are the basis of its operations, and the customer experience is based on aligning these in particular ways. This is already the case at low level in the self-routing algorithms in IP networks, and as algorithms develop, will appear at higher levels of service provision. In this situation, AI offers the potential to augment human capability, enabling human beings to manage a scale of network which cannot be managed any other way, within a practical time, let alone economically. Network virtualisation will drive this equation even further, using technologies such as service orchestration. The human contribution has the potential to be augmented to manage operations at a systems level (as opposed to task level), and at the level of proposition development and techno-economic innovation (rather than primarily at the design level).

- *a misconception that it's all about the algorithm and not the person.* Sometimes AI algorithms are 'black-box' in nature and so not transparent. Thus although the outcomes of many AI algorithms can be evaluated by humans, often the ways in which the results are arrived at cannot. This can be especially challenging when network planning and optimisation decisions involve a range of seemingly unrelated and disparate criteria for solution acceptance where many cannot be explicitly articulated. Despite this, it is important that results of automated optimisation and network planning approaches should engender the trust and acceptance of human engineers and decision makers. As has been pointed out previously by Klien et al. [4], the decision maker and any artificially intelligent tool must use common ground to work jointly to agreed goals. Klien et al. suggest that *"to be a team player, an intelligent (software) agent, like a human, must be reasonably predictable and reasonably able to predict others actions"*. It seems likely that human engineers and decision makers may be reticent to apply AI approaches they cannot control and that produce solutions that do not look ones that could feasibly have been produced by humans. Where trust and acceptance of such AI-produced solutions is missing, some commentators have recently have even reported on the *"tyranny"* of AI algorithms driving human behaviour [5].

In this paper, we are motivated to address such concerns and misconceptions from the perspectives of its three authors, i.e.

1. the *telecommunications network operator*, where innovative yet pragmatic solutions to networking challenges are required in constrained and demanding timescales;
2. the *telecommunications network planning and optimisation tools vendor*, where novel yet effective tool frameworks and applications are required to lead in the market place; and
3. the *academic researcher*, where robust evaluation of novel optimisation and machine learning algorithms requires the use of case studies and empirical benchmark problems of realistic scale and complexity.

To address these concerns and misconceptions, we present two relevant case studies in the following section (section 2), and then analyse the case studies' findings in section 3. Finally, we conclude and looking forward, offer suggestions in section 4.

2 Case Studies

2.1 BT Research Laboratories: Migration Project

BT research laboratories recently conducted a project to make its organisation 'AI ready'. Key to the project was the use of sophisticated data-driven decision tools known as 'boundary objects' to bring disparate business interests together, creating order of magnitude improvements in innovation and action. The study pointed to key components of an 'AI ready' organisation as being leadership, purpose, self-organisation, boundary objects together with cross-functional working, innovation, creativity, communications and culture. Change, in this context, encompasses technology developments, responses to markets or customers, and related internal changes. The design principles of the project differed from those which characterise more static organisations which deliver to markets of slow or unchanging products and technologies.

BT has successfully operated their Switched Telephony Platform for several decades. Over that time, a very efficient organisational machine had evolved to create high levels of efficiency and customer service through the regular activities that deliver and maintain service. These ran most efficiently as separate work flows, each with well-understood parameters (i.e. operational, financial, technical and cultural). Any interdependencies were minimised to simplify the flows of work. However, this area was required to be instrumental in one of the largest scale and most complex changes that BT has undertaken. PSTN is migrating to IP Voice, involving millions of customers, hundreds of employees and billions in revenue.

It was quickly realised that the existing structure and culture of the organisation – honed for efficient service delivery in a more stable world – would not be capable of delivering against this very different challenge. High levels of innovation would be necessary to create solutions never before envisaged, based on the distributed expertise and local knowledge of the whole team. Most significantly, the "team" would be redefined to include all those with an influence or contribution to make including other platforms, finance, strategy, and field operations etc., not simply within each activity-based sub-unit. The scale of innovation required all areas to flex and adjust so as to deliver to an overall business purpose over and above local historical "rules" which applied locally. Interdependencies emerged to be a key feature, to be constructed in sophisticated ways that allow each area to understand the effects of putative strategies across the whole business. To quote Howard Jacobsen, "conversations should be based on adjustment, not assertion". The concept of "Team of Teams" has been described in the so-titled book by General Stanley McCrystal of the US war on insurgency. Both these concepts have been shown to work with great effect in the migration project. Self-organising cross-functional team working was mediated by the Boundary Object Customer and Service Model (CASM) (described below) and delivered huge value. Key to this was making visible and cogent the higher purpose of the programme as a whole, with a corresponding loosening of the grip on local historical and habitual rules and targets which obscure and prevent a better global optimum. Significant accommodations have been made by the different business areas, which have enabled a transformation of the business value.

Based on rigorous organisational thinking, CASM combines data from many different BT business domains and allows the exploration of scenarios based on the human insight and imagination of the multi-disciplinary team. The significant benefit of this tool is its role as a boundary object, bringing together different disciplines. Instead of negotiating using PowerPoint and Excel, running separate off-line studies and applying a set of local rules which lead to a sub-optimal global solution, the different parties can explore the mutual effects of different storylines. Scenarios, inspired by the AI in the CASM tool, innovated by the participants can be run in real-time so that the context can be maintained in the group. This maintenance of mutual context is a crucial capability, well known to psychologists. It means that solutions of much greater subtlety – but much greater impact – can be discovered by the team together. The model provides a continuous sense of the real-world constraints, because it is connected to the data and a suite of sophisticated algorithms representing the technical and business characteristics and capabilities. Using a flying metaphor, a pilot uses the joystick not only to control, but importantly is provided with a feel of the forces on the control surfaces. This is crucial, and in stark contrast to suddenly coming across a hard constraint late in the day. The solutions found are therefore found in action (or in flight) and so make use of the tacit knowledge of the whole cross-business team, steered by the reality in the data and model. The solutions are thus emergent and cannot be pre-conceived and imposed arbitrarily, but come from the concerted expertise of the self-organised team. The solutions found speak for themselves. When the scenario is agreed, CASM is powerful enough to generate the line-by-line migration plan over the entire migration. It can be re-run whenever the business or the network sees a change that warrants investigation. The process has generated solutions which were previously invisible, and which have been implemented, saving tens of millions of pounds so far. This figure is likely to be significantly higher in the near future.

Two points about CASM (and boundary objects) became apparent:

- CASM data needs to be properly curated. The creation of the model, with its internal checks, revealed that significant data holdings in the company were crucially errored, poorly described, or originally non-existent. The building of the model also encouraged a more rigorous expression of technical and business rules. Building the model enabled us to correct these shortcomings. This indicates what will be increasingly important roles in the future BT. Our information systems need a new degree of rigour supported by specific roles, otherwise the company will miss out on massive business benefits of this kind.

- The role of a rigorous approach to organisational modelling, which underlies the power of the combination of boundary objects and self-organised teams, is crucial. The law of Requisite Variety states that if we need our "system" to navigate a complex ("high variety") environment, we need a "controller" for the system of equivalent variety. This has been created in the migration project through the special mix of human creativity and computer model, working as a multiply-connected network. The creation of emergent new solutions is not simply the co-ordination of the different activities across the business, but rather their integration. This integration is not only between different areas (Operations, Finance, etc.) but also across different timescales. The choice and specification of the engineering activity today is based on optimising the whole migration over the many years it will take. Indeed, the first benefits of this way of working have resulted from exactly this. Simply by specifying business-as-usual engineering tasks to be done in one of two (otherwise entirely equivalent) ways, huge amounts of future compaction work is avoided. This choice is also made in a way that increases customer service levels in the future. Thus the strategic direction and the day to day operations are connected and mutually optimised.

2.2 Aria Networks: Complex Multi-layer Optimisation

The Facebook backbone provides connectivity between different sites in the network to enable the social network, and typically requires IP/MPLS services to be carried over a fibre optical network under the sea and over a terrestrial mesh distributed around the world. Due to its large exposure radius, this geographically distributed infrastructure is prone to failures. Since failures are inevitable, any design and plan for the infrastructure should account for recovery mechanisms in the face of failures. Traditionally, operators design networks with protection in IP layer using rules of thumb built around parameters like topology, traffic, hop lengths etc. The majority of the network plan is manually designed, and often lacks a benchmark to assess its optimality. The algorithmic complexity of a holistic multilayer design makes it difficult for software tools to scale up and model a worldwide production network, taking into account its policies and constraints. The Facebook backbone has been witnessing a dramatic growth in traffic and the simplistic approach of optimizing each layer in the stack separately would lead to a sub-optimal network plan and unacceptably high network spend. To maximize the utility of deployed network hardware, it's important to leverage the flexibility offered by every layer and this makes a strong case for multilayer planning.

To reduce infrastructure costs and still meet service availability guarantees, one of the architectural entities to be evaluated is the adopted failure resilience model [6]. Failure resilience is available in both IP/MPLS and optical layers. IP Fast Reroute and MPLS Fast Reroute are shared protection mechanisms available in the higher layer (termed L3) that can guarantee protection within sub 50 msec. The Optical layer (termed L0) supports 1+1 protection feature that guarantees sub 50 msec recovery, but does not share resources. Optical restoration allows sharing of spectrum by different services across failure scenarios but restoration times can be high, at times, as long as a few minutes. The backbone has a mix of high priority and low priority support services. The high priority services have stringent availability requirements. Accumulation of downtimes, due to long restoration times, is not acceptable for these crucial services in the time window of availability measurement. Such long restoration times, however, may be considered a reasonable trade-off for low priority support services. One of the questions that we try to address while solving the multilayer design problem is to classify services based on their availability requirement, and identify which layer should be used to recover from failures, when each layer has its own resilience capabilities.

The multilayer design problem has an objective of minimizing total cost of ownership (TCO) of a network and consists of the following four sub-problems:

1. Topology design sub-problem, which requires the identification of optimal router bypasses and terminations in the IP topology.

2. L3 routing sub-problem, which requires the identification of optimal path to be taken by the IP services on the IP layer.

3. L0 express design sub-problem, which requires the identification of optimal optical bypass in the physical topology under steady state and failure scenarios.

4. L0 routing sub-problem, which requires identification of the optimal path to be taken by the services in the L0 layer. Ideally, in all these sub-problems, the algorithm should consider paths beyond the shortest paths in both L0 and L3, and optimality should be with respect to the global objective of network TCO, but this leads to a state space explosion even for a medium sized network. In the algorithm we designed for this study, we analyse paths beyond the shortest paths only in Layer 0, which in itself improves quality of our solutions significantly.

Algorithms had been developed previously to tackle this complexity but in the situation of Facebook's network with real services, business constraints and vendor choices, the modelling problem quickly became intractable. Although the team working on the problem at the time were unaware of it, they used domain knowledge of the engineer and AI algorithms in an iterative process to arrive at a solution that could easily be checked, i.e. it is easier to recognise a good result than it is to generate one. Using this framework, and distributing resilience between IP and optical layers, TCO savings in excess of 25% in the Facebook worldwide network were achieved. From the evidence in this case study, it seems highly likely that this result could not have been realised by humans or AI acting in isolation.

3 Analysis

In examining these concerns and possible misconceptions in the light of the BT case study, analysis reveals a number of causative factors which impact the situation. We find two orthogonal dimensions underpinning the problem i.e. (i) the number of objectives required for appropriate optimisation and machine learning, and (ii) the various stages of the network planning and optimisation life-cycle process. Typically, optimisation algorithms may be *single objective* (i.e. where solutions are optimised using a single objective fitness function), *multi-objective* (i.e. where solutions are optimised by trading-off two to four objectives), or *many-objective* (i.e. greater than four objectives are traded-off). The stages of the network planning and optimisation life cycle process include design, configuration and operations wherein the concerns of the algorithm, ownership and acceptance are relevant, respectively. We also find that addressing automation bias plays a role in promoting engineering satisfaction and so job security.

3.1 Number Of Optimisation Objectives

Regarding the number of objectives required for AI in the form of optimisation and machine learning, the first case is when the target can be distilled into a single value (i.e a single objective optimisation). This might typically be a cost minimisation, or to maximise a service level. In this case, the process is sufficiently self-contained that the pursuit of a single goal can be achieved without raising risks elsewhere. The human process involves negotiating the nature and value of the target level, and the statistical analysis needed to identify which parameters the system needs to measure and which parameters to affect in order to achieve the goal and receive feedback. This combination of analysis and business domain knowledge and judgement takes time in the set-up. Thereafter each service instance can be assessed in comparison with the cohort of statistically similar events in the past in order to make decisions on which action. After the set-up time, the individual decisions can be made in "reflex" time by computers.

The second case arises when there is a need for balanced objectives, and when that balance may be changed by the business or the environment (i.e. multi-objective optimisation). For example, there may be a need to balance cost and service level requirements. In this case there is the analysis stage and interaction with the business, but this time it involves achieving a compromise between business interests. This compromise is informed by analysis of the AI optimisation data which reveals the locus of practical compromises which are actually achievable by the system. Whenever the business may decide to modify this balance, for example to increase customer service levels and to absorb a certain increase in costs, the analysis and business negotiation needs to be revisited. The system again takes part in the negotiation between domain owners by revealing whether each proposed balance is achievable by the system. In this second case the assessment of each process event can happen in reflex time, but a change to the balance of targets requires a longer human negotiation and analysis period.

The third case concerns very complex business decision making (i.e. many-objective optimisation). In this case the search space of the problem is combinatorically huge, and beyond the capabilities of computation in any sensible time – even if it were possible to reduce all the targets to numeric values. Take for example the major platform migration described in the BT case study described above. The detailed sequence and timing of customer and technology moves affects the engineering cost rate, customer service levels, the rate of reduction of running costs (e.g. electricity), the time-profile of critical skill requirements, new technology deployment and rollout, maintenance profiles etc. In the recent BT case study example of a major (multi-£Bn, multi-year) migration, the potential combinatorial space exceeded 10^{50} and so cannot even be generated and stored, let alone inspected for optimal trajectories. Some objectives are numeric, others are not. The business balance is only achieved by a social process involving mutual adjustments and agreements to achieve the desired overall goal. The crucial enabler was a decision tool which allowed the multi-domain "super-team" to ideate and test scenarios through a live storyboard. This allowed the team to carry context a rich developing context throughout each exploration. The tool generates the relevant subset of the combinatorial optimisation space – a now more manageable quantity of data. A change to a new story results in some hours of computation, which can be inspected for its consequence on each business domain in near real-time. This in turn steers the creation of intuition and stimulates new innovative solutions, each informed and influenced by the reality of the system under consideration (the platform migration in this case). The time taken in this third case is determined by the human process of interaction and negotiation (an initial model building and data harvesting), not by computation speed. Rather, powerful computation has acted instead as the boundary object which is instrumental in the social process of creating and assessing options and showing their likely consequence on each of the business domains, and on the overall high level business goal. This discussion shows that from the simplest to the most complex application of AI-type technologies to real business optimisations, all require a human-centred process comprising an intimate mix of domain and analytical techniques. Each of the three stages we have identified requires a specific pattern of these interactions, which is both quantitative and qualitative. The "human-in-the-loop" is necessary here not only on ethical grounds nor additionally for the achievement of maximal value. Consideration of these techniques in the real business environment proves that it is needed for the system to function at all.

3.2 Stages of Network Planning

Evidence from the case studies suggests that network planning cannot be considered in isolation from the services or from the business. Unfortunately, however, there is also anecdotal evidence that network planning is frequently done taking into account equipment placement, communication protocols and single constraints like metric cost in IP networks or delay in traffic engineered networks. Where there is a trade-off between constraints a frequent outcome may be overbuild or at best the network is initially designed taking into account business constraints but not subsequently managed in a similar way as business needs evolve as they naturally do to remain competitive. In addition, network planning is not only an operational requirement but should occur along the service product life cycle wherein service means anything the operator exposes to their customer, e.g. connectivity, video distribution or 5G network slice. In analysing the evidence of the case studies, we can thus separate the product life cycle into 3 parts, i.e. service and network design, demand forecasting and operational maintenance.

- In the *service and network design* stage, many exploratory 'what-if?' questions arise. For example, what service profile should be engineered? What is/are the appropriate network architecture, relevant vendors, service price points? What hard and soft constraints are important for the business, and what options are available for leasing or building capacity? These are all important questions but very quickly they result in a combinatorial explosion of options. At this point AI (e.g. optimisation and machine learning) and humans can work together collaboratively, with humans dynamically steering the AI algorithms to explore and discover novel candidate solutions. Using human insight from domain knowledge which might otherwise be difficult to articulate, options may be contrasted, perhaps prompting trade-off decisions not previously considered and allowing human ingenuity to optimise a problem wherein many constraints exist. In the case study of multilayer network design described earlier [6], savings of 25% were achieved when compared to the best human designed network for Facebook's IP-Optical data centre network. At the end of the service and network design stage, two main deliverables are achieved, i.e. a network designed for the services and business model, and an AI-derived model that has been trained on "what good looks like" for the network operator.

- The *demand forecasting* stage takes the satisfactory business model developed in the previous stage and takes inspiration from marketing to explore where equipment might be placed to maximise revenue on a month/quarter basis or more frequently in virtual networks. In this stage, the AI algorithms require further configuration, tuning and adapting to the new constraints of the dynamic problem space, and again, domain knowledge from the human is crucial. As potential solutions emerge, human expertise provides input for the changing circumstances but remains compliant with the needs of the business. For example, it may be legitimate and advantageous to vary service uptake from that originally planned, or there may be a requirement to make use of supply chain changes.

- Finally in the *operational maintenance* stage, especially in the virtual networks or dynamic environments anticipated in 5G and IoT based services, the human engineer will not have time or capacity to engineer all aspects of running the network. This already happens, albeit in the more constrained environment of IP where network protocols are left to determine the optimal path through large networks. In this operational maintenance situation, AI algorithms collaborate with humans by dynamically routing and designing and networks in real time (reflex time), freeing to human engineer to focus of trade-off decisions between high level objectives and KPIs such as failure vulnerability or overall latency. Is is also possible to instruct the AI to self-tune and adapt to the dynamics of operational maintenance. In these ways, our analysis leads us to emphasise the valuable and essential partnership between humans and AI. We have found that this is one instance where the result is much greater than the sum of the individual parts.

3.3 Automation Bias

Analysis also reveals a further causative factor to be automation bias. For example, Lyell and Coiera [7] suggest *"automation bias (AB) happens when users become over-reliant on decision support, which reduces vigilance in information seeking and processing"*. The ideas of automation bias and user complacency in automated decision support have been reported previously [8, 9], and investigations performed by Bahner et al. [10] show that the perception of false recommendations is linked to high levels of user complacency. Shackelford [11] advises that an over-reliance on repeated human 'in-the-loop' evaluation and interaction in optimisation can result in user fatigue, wherein a lack of user focus results in inefficient discovery and optimisation.

In addition, it can be challenging to elicit subjective evaluation of qualitative factors in optimisation. Indeed, there are some ill-defined aspects of good software systems quality that cannot be articulated, but nevertheless 'you know it when you see it'. This phenomenon has been referred to as the *"quality without a name"* [12], and is endorsed by the software design patterns community [13]. In addition, it is usual for the decision-maker to employ many preferences and evaluation criteria during interaction. To exploit this valuable information, multi- and many-objective optimisation approaches (described above) are well suited.

To address automation bias and the difficulties of eliciting ill-defined aspects of solution quality, we note that attempts have been made previously to engage the decision maker by including their participation "in-the-loop" of the optimisation process. Exploiting decision maker insight via interaction within optimisation can enrich the fidelity of fitness evaluation, and improve performance by steering optimisation to human-preferred options, as well as guiding parameters of the optimisation process itself. In one sense, an interactive discovery of optimisation solutions is taking place, as was seen in the BT case study. Indeed, the notion of exploiting human interaction in optimisation is not new. Examples can be found in the AI optimisation technique of evolutionary algorithms. For example, Dawkins introduced computational biomorphs [14] while Sims suggested evolutionary virtual creatures [15]. A survey of interactive evolutionary computation was performed by Tagaki in 2001 [16]. Subsequently, in 2007, Branke et al. report on research into interactive multi-objective optimization [17]. A recent report in 2018 surveys interactive AI optimisation as part of the software engineering process [18].

In addition, some promising research on interactive optimisation and discovery in software design has been conducted at the University of the West of England, Bristol, using both evolutionary computing and ant colony optimisation. When designing software, there are many quantitative measures of success e.g. size of software, coupling between modules etc. However, the qualitative preference of the user is also crucial e.g. for recognising the symmetries and elegance of software design patterns. In this research, combining the quantitative measures with human evaluation of aspects such as elegance and understandability in an interactive multi-objective optimisation algorithm has resulted in the production of software that is not only superior to human-developed baseline software, but looks like software that might have been produced by a human-developer. By interacting "in-the-loop", the software designer discovers insights into the problem at hand, is in control of the evolutionary optimisation, and increasingly accepts and trusts the evolving candidate solutions presented by the algorithm [19, 20]. Lastly, we note that these findings resonate greatly with those of the BT and Aria Networks case study, wherein interactive contributions from both AI optimisation software, self-organising teams were necessary for project success.

4 Looking Forward

Firstly, we conclude that although introducing novel optimisation and discovery algorithms to telecommunications network planning can exploit significant advances in algorithm performance, it is essential to incorporate network engineer participation "in-the-loop", rather than excluding them from the optimisation process. We conclude that AI is well placed to assist and support the network engineer rather then replacing them.

Secondly, returning to the specific standpoints described in section 1,

- From the point of view of *telecommunications network operator*, we conclude that it's necessary to embrace an interactive, human "in-the-loop" optimisation framework to obtain solutions that are acceptable to network engineers to achieve the required operational performance gains;
- From the viewpoint of a *telecommunications network planning and optimisation tools vendor*, we conclude that provide leading-edge interactive optimisation frameworks capable of addressing large and complex telecommunications network problems will offer a compelling proposition to clients; and
- From the point of view of an *academic researcher*, we conclude that it's possible and indeed highly desirable to validate novel and innovative algorithms against case studies and empirical benchmarks of realistic scale and complexity, to obtain insights to further enhance the interactive algorithms.

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