Up to new limits: the number of petaflops nececessary for realistic health economic models

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Abstract

Objective: Health economic models (HEM) are used to assess the cost-effectiveness of healthcare interventions and inform decision-making by policymakers and payers. However, the complexity of these models is increasing, as they are increasingly analyzing more diverse and detailed datasets. This has led to a need for more powerful computational resources, including high-performance computing (HPC) systems. HPC systems allows to develop and to run HEMs in acceptable time frames and we describe the current status of such systems.

One challenge in determining the computer performance (expressed in petaflops) necessary for realistic HEMS is the wide range of model types and complexity. Some models may be relatively simple and require only a few petaflops, while others may be highly complex and require many more petaflops. Additionally, the amount of data required for a model can also impact the number of petaflops necessary.

Another challenge is the rapidly changing landscape of computational power. The number of petaflops available to researchers is increasing rapidly, and new technologies such as quantum computing may further increase the performance available in the future. This makes it difficult to predict the computing performance necessary for realistic HEMs in the future.

Despite these challenges, there are several strategies that can assess the computational power required for a particular model. One approach is to use existing models with similar complexity as a benchmark and adjust the computing performance accordingly. Another approach is to use trial and error, gradually increasing the number of petaflops until the model can run within an acceptable time frame.

Conclusion: Determining the number of petaflops necessary for realistic HEMs is a complex and evolving challenge. Further research is needed to understand the relationship between model complexity and the number of petaflops required, and to develop strategies for assessing the computational power needed for a particular model.

Introduction

Over the past 30 years, methodological and computational advances have allowed health economic models (HEMs) to become more sophisticated and to better reflect clinical reality. This growth has allowed for the inclusion of more variables, probabilistic sensitivity analyses, the use of Monte Carlo simulations and the exploration of more complex models (dynamic models, agent-based models, increase the number of health states, mixed cure models) resulting in more accurate and realistic models. Despite this increased complexity, the computing time has remained relatively constant, as improvements in computer technology have kept pace with the demands of these models. A mid-range processor can perform around 1 TeraFLOPS nowadays. This poster will explore the likely future computing power requirements, focusing on the potential need for PetaFLOPS and ExaFLOPS computers, as well as the role of cloud computing in supporting the continued growth and development of health economic models.

Figure 1. Old and new Supercomputers and Personal Computer

A: Cray Y-MP 1988 ~2.1 GigaFLOPS
B: LEONARDO 2022 ~100 PetaFLOPS
C: IBM PC 1985 ~100 KiloFLOPS

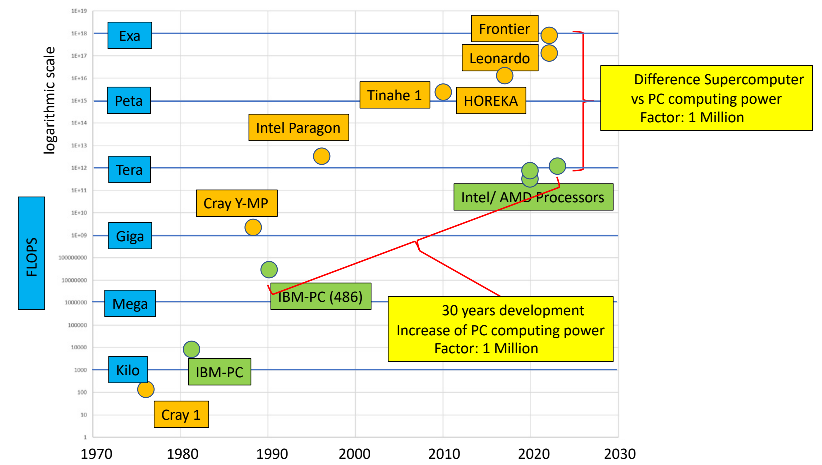
Complexity

The development of increasingly complex health economic models, coupled with the exponential growth of input data generated by digital health technologies, is leading to a significant increase in computational demands for modeling and simulation approaches. Wearables and other digital health technologies can generate large amounts of data, providing detailed information on individuals' health status and behaviors, but processing and analyzing this data requires sophisticated statistical and computational methods, which can be time-consuming and resource-intensive [Dahabreh, I. J. et.al., 2015; Yun, J., et al, 2020].

Furthermore, the increasing complexity of health economic models can exacerbate the computational demands of these models. For example, models incorporating dynamic disease progression and treatment effects or individual-level heterogeneity in health status and behavior require more complex algorithms and simulation methods to estimate parameters and generate predictions, which can further increase computational demands [Liu, F., et al., 2017].

The inclusion of real-world data (RWD) and the increased access to electronic health records (EHR) increases the complexity of clinical effectiveness evaluations. RWD can provide valuable insights into patient outcomes and treatment patterns in real-world settings, but the quality and completeness of the data can be highly variable and require careful cleaning and processing (Weiskopf, N. G. et al., 2013). Similarly, increased access to EHR can facilitate the collection of large-scale data on patient characteristics and treatment outcomes, but integrating and analyzing this data can present significant challenges due to the heterogeneity of EHR systems and the complexity of the data (Patel, V. et al., 2018).

Figure 2: Development of the computing power over time and the comparison of PC power and High-Performance Computers. HPCs have the computing power which is necessary for future health economic models closer to reality including the nowadays available data



Orange = High Performance Computers

Green = Personal computers, processors used in personal computers

Recent advances in computing technology, such as cloud computing and high-performance computing clusters, have enabled more efficient processing of large datasets and more complex models [Dahabreh, I. J. et.al., 2015; Yun, J., et al., 2020; Liu, F., et al., 2017]. Cloud computing, in particular, enables researchers to analyze large datasets and more complex models while easily keeping up to date with the evolution of computing technology, power and security, for a fraction of the cost of on-premise high-end computers. High-performance computing clusters can reduce the time required to run complex simulations and analyses, allowing researchers to more quickly explore different scenarios and assess the robustness of their models for more complex drugs mode of actions in a more and more specific therapeutic areas (e.g. gene therapy).

Furthermore, machine learning and artificial intelligence may offer new opportunities for the development of more efficient and accurate modeling approaches in the future [Dahabreh, I. J. et.al., 2015; Wang, S., et al., 2019]. Machine learning algorithms can analyze large and complex datasets, identify patterns, and predict outcomes more efficiently and accurately than traditional statistical methods. Similarly, artificial intelligence techniques such as neural networks and deep learning may enable the development of more sophisticated and accurate models.

In conclusion, the increasing complexity of health economic models and the growing volume of input data generated by digital health technologies are likely to increase the computational demands of modeling and simulation approaches. However, recent advances in computing technology and data analysis methods offer opportunities to meet these challenges and develop more efficient and accurate models. These developments may enable researchers to more effectively assess the impact of health interventions and inform policy decisions in the future [Dahabreh, I. J. et.al., 2015; Yun, J., et al., 2020; Liu, F., et al., 2017; Wang, S., et al., 2019; Kolasa, K. et.al., 2023].

Number of Variables as Measurement of Complexity

Health economic models have become more complex and sophisticated compared to models in the 1990s, with larger numbers of variables, the use of probabilistic sensitivity analysis, and more advanced survival analysis techniques. Probabilistic sensitivity analysis, which simulates uncertainty in multiple input parameters using Monte Carlo methods, has become a standard method in health economic modeling, while deterministic sensitivity analysis was the primary method used in the 1990s. Survival analysis remains an important technique, with a shift towards more advanced methods such as multi-state modeling, which can capture more complex disease pathways and treatment effects [Garrison Jr, L.P. et al., 2016].

In the 1990s, models were simpler and less rigorous, with limited use of probabilistic sensitivity analysis and reliance on deterministic sensitivity analysis and survival analysis techniques. However, they still played an important role in informing healthcare policy and decision-making at the time [Roberts, J. et al., 1999; Garrison Jr, L.P. et al., 2007; Weinstein, M.C. et al., 2003].

Today, health economic models typically include a larger number of variables. For example, a systematic review of cost-effectiveness studies published between 2000 and 2015 found that the median number of variables included in models was 62, with a range of 10 to 593 [Garrison Jr, L.P. et al., 2016]. This increase in the number of variables included in health economic models has led to a more comprehensive assessment of the cost-effectiveness of healthcare interventions.

Probabilistic sensitivity analysis has become a standard method in health economic modeling, allowing for a more comprehensive assessment of uncertainty. A study by [Garrison Jr, L.P. et al., 2007] found that the use of PSA in cost-effectiveness studies increased from 17% in 1995 to 70% in 2005.

In summary, health economic models have evolved significantly over the years, becoming more complex and sophisticated compared to models in the 1990s. Today's models are characterized by larger numbers of variables, the use of probabilistic sensitivity analysis, and the use of more advanced survival analysis techniques. These models provide a more comprehensive assessment of uncertainty and can capture more nuanced aspects of disease progression and treatment effects, ultimately leading to more informed healthcare policy and decision-making.

Computing Time

The computing time required to run health economic models has decreased significantly over the past few decades due to advances in technology, such as faster processors, larger memory capacity, and more efficient algorithms. However, it is difficult to provide a precise estimate of typical computing time for models in the 1990s and 2010s because it can vary widely depending on the complexity of the model, the size of the dataset, and the specific computing resources available.

In the 1990s, health economic models were typically less complex and had fewer variables than models today. The limited availability of data and computing power meant that models could take a long time to run, sometimes taking several days or even weeks to complete. Some models were run on personal computers or workstations, while others required access to high-performance computing clusters or mainframe computers.

In contrast, health economic models today are more complex and can incorporate larger datasets, making use of more sophisticated modeling techniques and probabilistic sensitivity analysis. While the computational requirements for these models are greater, the increased availability of high-performance computing resources means that models can often be run more quickly than in the past. For example, a study by Tarride et al. (2012) found that a cost-effectiveness model for colon cancer screening, which included probabilistic sensitivity analysis, could be run in a few hours using a standard desktop computer.

The computing time required for a given model will depend on the complexity of the model, the size of the dataset, and the specific computing resources available.

The computing time required to run health economic models with DecisionMaker (Pauker et al. 1991) and SmlTree (Hollenberg 1993) was minutes to hours, days and even weeks. Today all these models need a computing time of a fraction of seconds or a few minutes, but the complexity of these models were compared to today's models "simple".

Outlook and Conclusion

In conclusion, the exponential growth of computing power in health economic models over the past 30 years has enabled significant advancements in the field. As these models continue to incorporate digital health input data, real-time decision-making, and more complex methodologies, there is an irrefutable need for PetaFLOPS and ExaFLOPS. The development and adoption of cloud computing solutions will be critical for the continued growth and evolution of health economic models.

Today single digits TeraFLOPS are necessary for running HE models. The advancements in HE models, and the introduction of digital health needs the use of HPC = PetaFLOPS computers in order to get results within an acceptable time. HPC and cloud computer are necessary to tackle these challenges.

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