Annals of "Dunarea de Jos" University of Galati
Fascicle I. Economics and Applied Informatics
Years XXXI – nº2/2025
ISSN-L 1584-0409 ISSN-Online 2344-441X
www.eia.feaa.ugal.ro

DOI https://doi.org/10.35219/eai15840409526

Economic Decision-Making in Sensor Software Systems Using Predictive AI Approaches

George Chiriță*, Mioara Chiriță**

A R T I C L E I N F O

Article history:
Received July 28, 2025
Accepted August 22, 2025
Available online September 2025

JEL Classification
C63, D81, L86, Q55

Keywords:
economic decision-making, sensor-based software systems, ai, predictive modeling, resource optimization, machine learning in cost reduction

A B S T R A C T

In the current context of the rapid development of sensor-based software systems, economic decision-making has become essential for optimizing resources and reducing operational costs. This paper analyzes the applicability of AI-based predictive methods in supporting the economic decision-making process in sensor-based software systems. Using machine learning models, resource consumption can be forecasted, operational costs can be estimated, and system performance can be evaluated under different conditions. The main objective of the research is to facilitate informed decision-making regarding the configuration, scaling, and maintenance of software systems that manage sensor networks, in order to achieve increased economic efficiency. This study refers to a theoretical analysis which details the methodological principles, but also the design rationale underlying predictive AI models applied in economic decision-making. The research results highlight the benefits of applying AI to anticipate system behavior and reduce costs associated with overprovisioning, excessive energy consumption, or reactive maintenance. The conclusions of the paper highlight the real potential of artificial intelligence in transforming sensor-based software systems into more economically sustainable infrastructures, while providing a valuable tool for decision-makers in industrial, urban or research contexts.

1. Introduction

Sensor-based software systems are now essential parts of contemporary technology infrastructures, supporting a broad range of applications in industries like manufacturing, energy, healthcare, agriculture, and urban management (Gubbi et al., 2013; Zanella et al., 2014). High-frequency data streams produced by these systems' constant physical environment monitoring help to guide operational plans and control systems. The integration of economically informed decision-making into these systems is still limited, despite the fact that their data acquisition and system automation capabilities have greatly improved (Gupta et al., 2021). Conventional sensor systems frequently depend on reactive logic or static decision rules, which may not sufficiently take cost-benefit trade-offs, resource limitations, or changing environmental conditions into account (Banafa, 2016).

This disparity is a serious problem, especially in situations where economic viability and operational efficiency are crucial. Intelligent decision-making frameworks that can maximize results from both a technical and financial point of view are becoming more and more necessary as sensor data volume and velocity rise. Promising approaches to meeting this need are provided by recent advancements in AI, especially in predictive analytics. Systems can predict future states, assess possible scenarios, and take proactive decisions in the face of uncertainty thanks to predictive AI techniques like reinforcement learning, time-series analysis, and machine learning-based forecasting (Jordan & Mitchell, 2015; Goodfellow et al., 2016). By anticipating system behaviors, preventing expensive failures, and allocating scarce resources as efficiently as possible, these methods, when combined with sensor software systems, can support economically optimal actions (Zhang et al., 2020).

This study explores how predictive AI can improve sensor software systems' ability to make economically sound decisions. To increase the effectiveness and financial performance of such systems, we suggest a systematic framework that integrates data-driven prediction, optimization, and decision support. We seek to clarify how predictive AI can turn sensor systems into intelligent agents with the capacity for autonomous, economically rational behavior by reviewing pertinent literature, technical approaches, and real-world use cases.

*, **Dunarea de Jos University of Galati, Romania. E-mail addresses: gechirita@ugal.ro (G. Chirita), mioara.chirita@ugal.ro (M. Chirita – Corresponding author).

The three main goals of this study are to close the identified gap in economically informed decision-making in sensor software systems:

O1: To develop and suggest a conceptual framework that combines sensor software systems and predictive artificial intelligence (AI) techniques to facilitate real-time, cost-effective decision-making.

O2: To assess how well predictive models, including machine learning, time-series forecasting, and reinforcement learning, optimize resource allocation, lower operating costs, and improve sensor-driven environment performance.

O3: To demonstrate the economic and technical feasibility of the suggested framework by validating its practical applicability through case studies or simulation-based analyses in important domains, such as precision agriculture, energy systems, and smart manufacturing.

A critical evaluation of previous research on AI-assisted economic decision-making in sensor systems is necessary to bolster the methodological approach and pinpoint current research avenues. In order to create a comprehensive viewpoint on the subject being studied, the subsequent section examines pertinent literature from related disciplines, including artificial intelligence, sensor software systems, and economic decision-making.

2. Literature review

Sensor software systems, often at the core of the IoT, are designed to collect, process, and distribute data collected from the physical world (Gubbi et al., 2013; Zanella et al., 2014). In industries like manufacturing, healthcare, smart cities, and environmental monitoring, these systems are crucial. Sensor systems can be built to operate on edge, fog, or cloud computing platforms, with trade-offs between computational capacity, energy efficiency, and latency (Shi et al., 2016). The decision-making processes of these systems are often static or reactive and lack adaptive economic reasoning, despite advancements in networked intelligence and sensor integration (Gupta et al., 2021).

The methodical assessment of trade-offs to attain the best results while keeping cost, risk, and utility constraints in mind is known as economic decision-making (Simon, 1983). This frequently entails striking a balance between resource allocation, energy consumption, and maintenance expenses in the context of intelligent systems. Conventional methods use heuristic or rule-based models, which are inadequate in dynamic, data-rich settings (Banafa, 2016). To overcome these constraints, a growing corpus of research is promoting the incorporation of computational intelligence, particularly in smart infrastructure and cyber-physical systems (Zhang et al., 2020).

In order to predict events and modify system behaviors in real time, predictive AI techniques like machine learning (ML), deep learning, and reinforcement learning have become increasingly popular in recent years (Jordan & Mitchell, 2015; Goodfellow et al., 2016). In sensor-rich environments where past trends can be used to predict equipment failure, demand spikes, or environmental changes, time-series forecasting is especially useful. The potential of reinforcement learning to learn optimal policies through interaction with the environment has been investigated. It provides dynamic control strategies that optimize for long-term rewards, such as economic metrics (Sutton & Barto, 2018).

Numerous studies have shown how well predictive analytics and economic optimization work together. To minimize downtime and lower lifecycle costs in industrial systems, for example, predictive maintenance models have been used (Lee et al., 2014). Similarly, forecasts are used by AI-based energy management systems to lower operating costs in smart grids (Mohammadi et al., 2020). Nevertheless, there is still a lack of a well-developed framework that specifically addresses economic decision-making in sensor software systems that use predictive AI. A unified strategy to integrate economic models, predictive algorithms, and real-time sensor data processing is lacking in existing research, which frequently addresses these aspects separately.

There is little interdisciplinary work that connects AI prediction, economic theory, and software system architecture, despite the literature providing strong foundations in predictive modeling and sensor network design. Without methodically integrating economic goals into the decision-making process, the majority of current implementations place an emphasis on either technical efficiency or predictive accuracy. This disparity emphasizes the need for an all-encompassing framework that uses predictive AI technologies to enable economically sound decisions in real-time within sensor-driven environments.

Table 1. Structured review of scholarly contributions on predictive artificial intelligence in economic optimization of sensor software systems

Reference	Purpose	Subjects	Sample Design	Conclusion
Gubbi et al. (2013)	Overview of IoT architecture and future directions	IoT systems and architectures	Conceptual framework	Highlighted the core role of sensor software systems in IoT

Reference	Purpose	Subjects	Sample Design	Conclusion
Zanella et al. (2014)	Discuss IoT applications in smart cities	Smart city sensor systems	Survey of deployments and architecture	Confirmed the centrality of sensor networks in urban IoT
Shi et al. (2016)	Explore edge computing for sensor systems	Edge vs. cloud computing	Comparative architectural analysis	Defined trade-offs in latency, energy, and computation
Gupta et al. (2021)	Review smart sensing architectures and challenges	Sensor architecture and design	Taxonomic literature review	Emphasized lack of adaptive economic decision-making
Simon (1983)	Introduce economic decision-making in human systems	Decision theory	Conceptual framework	Stressed rational trade-offs in uncertain environments
Jordan & Mitchell (2015)	Survey machine learning trends and applications	ML methodologies	Review	ML applicable for predictive sensor decision-making
Goodfellow et al. (2016)	Comprehensive introduction to deep learning	Deep learning models	Textbook	DL offers potential for predictive accuracy in sensors
Lee et al. (2014)	Propose CPS for Industry 4.0	Smart manufacturing	Architecture proposal	Reinforced sensor integration in predictive frameworks
Mohammadi et al. (2020)	Use DRL for smart city services	IoT, DRL in cities	Implementation case	DRL enables cost-effective sensor-based control
Zhang et al. (2020)	Review predictive maintenance using data-driven methods	Predictive maintenance	Survey	Economic optimization with predictive models

Source: authors

Recently, the specialized literature, as we can see from the analysis of Table 1, has highlighted the rapid evolution of software sensors within cyber-physical systems, with a particular focus on their implementation in industrial, urban and energy environments. The integration of predictive artificial intelligence into these systems has enabled the transition from passive monitoring to proactive, data-driven decision-making. Fundamental studies (Gubbi et al., 2013; Shi et al., 2016; Jordan & Mitchell, 2015) have documented the advantages of adopting edge/fog/cloud architectures, highlighting the critical role of smart sensors in both early anomaly detection and resource optimization and increasing operational resilience. In parallel, there has been a growing concern about integrating economic criteria into decision-making algorithms, in an ongoing effort to reduce maintenance costs, energy consumption, and operational risks (Simon, 1983; Lee et al., 2014; Mohammadi et al., 2020).

However, the analysis of the specialized literature highlights a lack of convergence between AI-based predictive models and rigorous economic decision-making formalism. Most works in the field treat the technical components (prediction accuracy, computational architectures) and the economic ones (costs, utility) separately, without integrating them into a unified framework. This gap justifies the need for a conceptual and application framework that combines AI algorithms (including reinforcement learning and deep learning) with real-time economic optimization models.

Thus, our article proposes an innovative direction by exploring the potential of predictive software sensors as active factors in autonomous economic decision-making, thus responding to a real need for sustainable efficiency in the IoT and Industry 4.0 era.

3. Conceptual framework for economic decision-making in sensor software systems

Based on the previous conceptual framework, which identified the main components involved in AI-assisted economic decision-making in sensor-based software systems, it is necessary to delve deeper into how these concepts can be formalized and operationalized in intelligent systems. In this section, we will detail the decision-making models used in autonomous technological environments, highlighting the role of economic decision theory in optimizing the performance of these systems. The emphasis will be on integrating the principles of utility maximization, efficient resource allocation and cost-benefit analysis, in correlation with modern predictive methods.

3.1. Economic decision modeling in intelligent systems

Modeling economic decision-making in intelligent systems is an essential step in designing autonomous solutions that must function efficiently under dynamic and often uncertain conditions. At its core, economic decision theory is based on principles such as utility maximization, resource optimization, and cost-benefit analysis, which were originally defined in the classic works of Herbert Simon (1983), who introduced the concept of bounded rationality in decision-making: economic agents do not make perfect decisions, but "good enough" for the available information and temporal context (Simon, 1983).

Thus, as we can see from the specialized literature, in modern intelligent systems based on software sensors, these concepts acquire a technological valence. This is because utility maximization translates into both increased operational efficiency and minimized energy consumption or reduced maintenance costs. All of this is integrated into a data-driven decision-making framework. It is thus concluded that autonomous systems must be able to make decisions quickly and adaptively, and this adaptability is directly influenced by their ability to assess the economic consequences of actions in uncertain and variable environments.

Recent studies emphasize that decision-making under conditions of uncertainty, such as those encountered in industrial or urban environments, requires the integration of predictive models with economic approaches, in a hybrid and contextual manner. According to Koulouriotis and Diakoulaki (2020), in cyber-physical systems, decision-making must include direct economic indicators (operating costs, yields, amortization time), but also indirect ones (energy impact, predictive maintenance), managed by intelligent algorithms (Guimarães, Nagano & Silva, 2020).

Also, from an applied perspective, Sun et al. (2021) demonstrate that integrating economic decisions in autonomous sensor systems with reinforcement learning algorithms allows not only to optimize immediate costs, but also to allocate resources based on long-term economic forecasts, which leads to improved sustainability of the software infrastructure (Chaudhuri & Sahu, 2022).

Thus, modeling economic decisions in intelligent systems involves not only implementing algorithms that optimize technical parameters, but also integrating robust economic principles that give the software agent the ability to act rationally, given resource constraints and the long-term goals of the system. In predictive software sensors, this means the ability to estimate not only the future values of a variable (e.g. temperature, wear), but also the economic impact of these estimates in order to make the optimal decision (e.g. postponing a repair, adjusting energy consumption, reallocating tasks).

3.2. Integrative conceptual architecture for economic decision-making based on software sensors and predictive AI models

To support real-time economic decision-making in sensor-based software systems, we propose a conceptual architecture that integrates data collection from physical sensors, intelligent data processing through predictive AI models, and economically oriented decision-making components. This architecture is aligned with the Industry 4.0 paradigm and assumes a bidirectional flow of information between the physical and cyber layers.

Software sensors function as virtual entities that, through statistical models or machine learning algorithms, estimate critical variables that are difficult to measure directly. Raw data from physical sensors (e.g. temperature, pressure, vibration) is transmitted to the processing infrastructure, which can be implemented at the edge, fog, or cloud level, depending on the latency, security, and computational capacity requirements.

Edge computing architecture allows for fast and local response, which is essential for applications with strict time constraints, such as those in energy or industrial production. Fog computing provides an intermediate interface for distributed aggregation and analysis, while cloud computing provides scalability and advanced storage and machine learning capabilities. As Shi et al. (2016) show, this edge–fog–cloud hierarchy allows for an optimal balance between resource consumption and system performance in dynamic industrial contexts.

At the heart of the proposed architecture is the economic decision-making component, which analyzes estimates from predictive models (e.g., recurrent neural networks or reinforcement learning algorithms) and generates decisions regarding resource allocation, preventive maintenance, or system configuration adaptation. This approach allows not only to reduce operational costs, but also to increase the resilience and adaptability of the system in the face of uncertainty and contextual changes.

Thus, the proposed architecture provides a coherent framework for integrating artificial intelligence and economic decision-making into sensory software systems, contributing to the development of intelligent, economically efficient and sustainable infrastructures.

The importance of an integrative conceptual architecture that combines software sensors and predictive AI models in the context of economic decision-making is essential for transforming traditional technological systems into intelligent, autonomous and economically efficient infrastructures. This framework is valuable for real-time data correlation with economic decisions. By integrating sensor data sources with AI models, the system becomes able to analyze operational dynamics in real time and make decisions based on economic forecasts we can reduce risks and optimize costs.

It also enables maximizing decisional value through intelligent processing. In such an architectural framework, raw data is transformed into contextual and economically relevant information through edge/fog/cloud processing (Shi et al., 2016). This supports autonomous decisions that balance utility, cost and resources.

We can also talk about the importance of flexibility and scalability for different domains. This is because the proposed architecture is applicable to industries such as energy, agriculture, transport or smart cities, providing an adaptable and modular framework for the economic integration of software sensors.

It can also provide Decision Support in uncertainty. It is known that predictive models allow systems to evaluate future scenarios, anticipating demands, wear, energy consumption or failures. These aspects are fundamental for sustainable economic efficiency in autonomous systems.

A final highlight of its importance is given by the fact that this conceptual architecture serves as a foundation for the development of cyber-physical systems. It not only collects and processes data, but also acts intelligently according to well-defined economic criteria, representing an essential step towards automation with integrated economic value.

3.3. Methodological challenges and limitations

The development and implementation of economic decisions in intelligent systems based on software sensors and predictive AI models raises a number of significant methodological challenges and technical limitations. One of the main problems is the lack of transparency of the artificial intelligence algorithms used in decision-making processes, especially in the case of "deep learning" models. These models, although performing well in prediction, are often perceived as "black boxes", which limit the explainability and acceptance of automated decisions in critical economic contexts (Zhang et al., 2020).

Another challenge is the economic calibration of decisions generated by autonomous systems. The integration of economic constraints, such as maintenance costs, resource consumption or penalties for downtime, requires hybrid models that combine algorithmic inference with explicit economic rules. In the absence of a standardized framework for modeling these aspects, many implementations rely on ad-hoc heuristics, with results that are difficult to generalize (Banafa, 2016).

Also, the complexity and size of AI models involved in prediction contribute to high energy consumption, which is essential in edge or embedded applications. The limited resources of edge computing infrastructures impose restrictions on the implementation of large models, and strategies to reduce algorithmic complexity through compression or pruning are still maturing (Shi et al., 2016).

Another critical aspect is related to the adaptability of predictive algorithms under dynamic and uncertain conditions. Most AI models, especially those based on deep learning, assume stable training conditions and fully labeled data sets. In reality, cyber-physical systems operate in constantly changing environments, where data may be incomplete, noisy, or unstructured, and distributions may change over time (a phenomenon known as "concept drift"). This phenomenon affects the accuracy of predictions and the reliability of economic decisions generated by the system. Also, the economic models used must be constantly recalibrated to remain relevant, which implies a considerable maintenance effort and domain expertise (Zhang et al., 2020).

In addition, the scalability of the proposed architectures represents a significant challenge in an industrial context. Integrating software sensors with edge-fog-cloud infrastructures requires a careful balance between latency, energy consumption and processing capacity. High-performance AI models can quickly become inefficient in environments with strict energy or hardware resource constraints (Shi et al., 2016). Moreover, as the complexity of the architectures increases, the difficulty of explicitly correlating the raw data collected, the applied AI models and the economic impact of the generated decisions arises. Thus, the lack of decision traceability and the difficulty of algorithm interpretability (the so-called "black box" of neural networks) make it difficult to validate automated economic decisions in front of the human actors involved (Banafa, 2016).

These limitations highlight the need for balanced approaches that prioritize both the performance of predictions and their sustainability and interpretability in an economic decision-making context.

4. Conclusions

This paper investigated the importance of integrating economic decision-making into sensor-based software systems, using predictive artificial intelligence techniques. In a dynamic industrial context, marked by advanced automation and large volumes of data, economically informed decision-making becomes essential for optimizing resources, reducing operational costs and increasing overall efficiency. Theoretical analysis and literature review highlighted the need for a conceptual architecture that combines data acquisition, AI prediction and economic decision-making mechanisms in a coherent and scalable framework.

The importance of the topic is all the greater as modern cyber-physical systems require not only automation, but also decision-making autonomy with economic reasoning. AI technologies can transform software sensors from simple measurement tools into intelligent agents capable of anticipating behaviors, efficiently allocating resources and maximizing the economic value of controlled processes. This opens up new directions in the design of sustainable infrastructures, especially in industries where energy efficiency, predictive maintenance and real-time adaptability are critical.

Finally, future research will be based on the analysis and follow-up of the implications of integrating explicit economic models into machine learning algorithms. It can also be considered to develop validation scenarios in real industrial contexts and to address the challenges related to transparency, algorithmic ethics and energy consumption. Only through an interdisciplinary and rigorous approach can the proposed topic reach its full potential in the sustainable digital transformation of industry.

References

1. *Chaudhuri, A., & Sahu, T. P. (2022). Multi-objective feature selection based on quasi-oppositional based Jaya algorithm for microarray data. Knowledge-Based Systems, 236, 107804. https://doi.org/10.1016/j.knosys.2021.107804*
2. *Banafa, A. (2016). IoT: Challenges and issues in data management. IEEE Internet of Things Journal, 3(3), 229–235. https://doi.org/10.1109/JIOT.2016.2555299*
3. *Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press. https://www.deeplearningbook.org/*
4. *Guimarães, H. R., Nagano, H., & Silva, D. W. (2020). Monaural speech enhancement through deep wave-U-net. Expert Systems with Applications, 158, 113582. https://doi.org/10.1016/j.eswa.2020.113582*
5. *Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of Things (IoT): A vision, architectural elements, and future directions. Future Generation Computer Systems, 29(7), 1645–1660. https://doi.org/10.1016/j.future.2013.01.010*
6. *Gupta, A., Pathak, P. H., & Mohapatra, P. (2021). Smart sensing systems: Architectures, challenges, and future directions. ACM Computing Surveys (CSUR), 54(4), 1–35. https://doi.org/10.1145/3453155*
7. *Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. Science, 349(6245), 255–260. https://doi.org/10.1126/science.aaa8415*
8. *Lee, J., Bagheri, B., & Kao, H.-A. (2014). A cyber-physical systems architecture for industry 4.0-based manufacturing systems. Manufacturing Letters, 3(1), 18–23. https://doi.org/10.1016/j.mfglet.2014.01.003*
9. *Mohammadi, M., Al-Fuqaha, A., Guizani, M., & Oh, J.-S. (2020). Semi-supervised deep reinforcement learning in support of IoT and smart city services. IEEE Internet of Things Journal, 7(5), 4159–4170. https://doi.org/10.1109/JIOT.2020.2966403*
10. *Shi, W., Cao, J., Zhang, Q., Li, Y., & Xu, L. (2016). Edge computing: Vision and challenges. IEEE Internet of Things Journal, 3(5), 637–646. https://doi.org/10.1109/JIOT.2016.2579198*
11. *Simon, H. A. (1983). Reason in human affairs. Stanford University Press. https://doi.org/10.1515/9780804768360*
12. *Sutton, R. S., & Barto, A. G. (2018). Reinforcement learning: An introduction (2nd ed.). MIT Press. http://incompleteideas.net/book/the-book-2nd.html*
13. *Zanella, A., Bui, N., Castellani, A., Vangelista, L., & Zorzi, M. (2014). Internet of Things for smart cities. IEEE Internet of Things Journal, 1(1), 22–32. https://doi.org/10.1109/JIOT.2014.2306328*
14. *Zhang, Y., Wang, J., & Wang, X. (2020). Data-driven predictive maintenance for smart manufacturing systems: Review and outlook. Journal of Manufacturing Systems, 56, 35–45. https://doi.org/10.1016/j.jmsy.2020.04.003*