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Title of the Doctoral Thesis:

THE DEVELOPMENT OF AN ADVANCED ENERGY MANAGEMENT SYSTEM

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THESIS SUMMARY

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1. Introduction

In the actual geo-political and market context, in which the energy trilemma: energy security – energy accessibility and sustainability becomes an essential issue at a world-wide level, the PhD Thesis ”The development of an Advanced Energy Management System” proposes a logical structure and a technical and financial model trough which energy end-users can identify, quantify (from a technical and financial point of view) and support the implementation of Energy Performance Improvement Actions (EnPIA) and Power Quality Indices Improvement Actions (PQIIA).

By implementing the Advanced Energy Management System (AEMS) proposed in the PhD Thesis, end-users can identify, in real time, potential actions for increasing their overall energy performance, mitigate potential Power Quality Indices issues and evaluate the technical and financial potential of implementing hybrid distributed-generation projects.

Real time analysis leads the end-user to a faster identification and implementation time for organizational (no cost or low investment cost) measures, whilst the medium to long term analysis leads to a better understanding of significant-investment measures and actions for increasing the overall energy performance. The former type of actions is thus better and more accurately evaluated and understood, from both a technical point of view and from a financial performance point of view.

All these aspects can lead to a significant decrease of the energy bought by the end-user and can thus lead to a significant increase in the overall profitability of the company which implements the proposed AEMS.

1.1. Legal framework

The European legislation, which is in a continuous process of increasing it’s transition towards sustainability ambitions, is the main reason for the necessity of developing the proposed AEMS, having the potential of becoming an important tool trough which end-users can meet the requirements and targets set by both the European and national legislation, in all relevant fields of actions: **energy efficiency**, **power quality** and **distributed energy generation**.

In order to identify the high energy-savings potential energy sectors in which AEMS can be implemented, an in-depth analysis of the main regulatory and legal framework regarding Energy Efficiency was conducted, doubled by an in-depth analysis of relevant scientific literature.

At a national level, the regulatory framework is elaborated by the Romanian Energy Regulatory Agency (RERA), based on the en-force primary legislation. A number of Laws, Decisions and Orders are currently regulating the energy efficiency field, the energy performance of buildings, the end-users obligations regarding periodical reporting procedures to relevant state agencies, the methods of promoting energy generation based on renewable energy sources and the energy services sector (energy management and energy auditing services).

The existing regulatory framework should lead an energy end-user towards an optimization of it’s energy performance indicators by the end of the period stated in the annual Energy Performance Improvement Plan (EnPIP). This objective is, however, hard to reach. The most important aspects which lead to a negative influence over the energy performance improvement actions efficiency and implementation rate include, but are note limited to: a lack of various energy flows monitoring / metering, the impossibility to corelate various types of energy uses with the final product / service of the end-user, a lack of a proper communication between the energy manager and the top management of the company, a lack of energy-education of all employees and a lack of interest regarding energy efficiency for companies in which energy related costs are not significant with regard to the overall costs.

As a mean of achieving the energy efficiency objectives, the International Standardization Organization – ISO – defined, conceived and elaborated a number of Standards which offer guidance for any type of end-user (industrial, tertiary, public or residential sector) in implementing an Energy Management System (EMS) adequate with their existing situation – the ISO 50001 – 50015 group of standards.

Late 2019, the European Commission decided that Energy Efficiency has to become a priority for the European Union – *Energy Efficiency First!*, the new target of energy efficiency increase being set at a minimum of 32.5% by the end of 2030, compared with the BAU scenario (Business As Usual), by including the obligation of obtaining energy-savings in the 01.01.2021 – 31.12.2030 in the current legislation, revising the existing regulations regarding thermal energy monitoring and billing and increasing the efficiency of heating and cooling processes. In order to achieve these objectives, the European Union proposes, as a first dimension of the solution, a moderation in energy demand.

In addition to this, in the second half of 2021, the *Fit for 55* legislative package was launched, through which the European Union proposes the increase of the target regarding climate-change mitigation. The EU proposes a new CO_2 certificate transaction mechanism for the transportation and buildings sectors by 2026, increasing the target of reducing equivalent CO_2 emissions from 40% to 61% by the end of 2030 (with a reference point set for the emissions levels of 2005).

Another new dimension of the EU is that "*Polluters Pay!"*, as detailed in the 2004/35/CE Directive, modified, and updated on the 17th of June 2020. This update states that any company which generates an environmental impact is directly responsible for it and must take all reparative or preventive measures, whilst integrally supporting the associated costs.

It is thus becoming extremely important for end-users to be able to monitor, with a high degree of accuracy, the environmental impact generated by their current activity, in order to be able to quickly identify the necessary preventive actions, thus minimizing the long-term costs generated by this new EU dimension.

Regarding the energy produced by using renewable energy sources, *Fit for 55* increases the target from 32% to 40% by the end of 2030. Energy efficiency is a top priority, the targets being raised from 32.5% to 36-39% by the end of 2030. The novelty of this package is that it stipulates that all Member States must ensure a decrease in energy demand (by increasing energy efficiency) by up to 9% by the end of 2030.

From an energy efficiency point of view, AEMS was implemented and tested in the energy boundaries of various types of end-users, both from the tertiary sector (office buildings), industrial sector and power-distribution sector (distribution system operators), as it will be shown in Chapters 3 and 4.

Through its energy demand forecast and energy performance evolution statistical analysis modules, AEMS acts as a tool for achieving the goals regarding energy efficiency and, implicitly, the transition towards sustainability of end-users.

In the thesis, a technical, energetical and financial evaluation methodology was proposed in order to quantify the impact of various Power Quality Indices over the energy boundary, thus proving that the consideration of some PQIs in the EnPIP stage is mandatory and essential.

In order to develop the PQI analysis modules, an in-depth analysis of the existing national and international regulatory framework for PQIs was conducted.

It was thus identified that PQIs which have a high potential of increasing EnPIs (such as current unbalances, current harmonic distortions etc.) do not have limit values set by en-force standards / regulations. Thus, a methodology for identifying the optimal variability of these PQIs in the analyzed energy boundary was proposed and tested, in order to lead to a maximization of the overall EnPIs.

The development of the AEMS was based on the principles presented in this chapter, based on the idea that an in-depth energy monitoring and metering procedure represents the foundation of any efficient EnPIP.

Even though AEMS's main objective consists in leading to an increase in the overall energy performance and, implicitly, financial profitability of the analyzed energy boundary, by doing so, AEMS can generate a domino's effect on a macroeconomic scale, by reducing the energy demand in the power distribution grids. A significant part of this energy is currently produced from conventional sources (polluting energy sources). Also, the reduction of the energy demand of end-users will also lead to a decrease in energy and power losses in the up-stream power distribution and transport grids.

1.2. General Objectives of the Thesis

The PhD Thesis elaboration was based on the necessity of developing an instrument (hardware and software) which is able to monitor relevant parameters, and which can lead to an increase of the energy performance of electricity end-users, with an adequate level of power quality and which can also support the implementation of distributed energy generation projects.

The thesis had the following General Objectives:

- **G.O.1.** In depth analysis and identification of the main concepts, indicators, regulatory framework and technical norms and standards necessary for developing the AEMS – bibliographic research was conducted in order to identify existing EMS, both in an experimental development stage (TRL<9) and in a commercial readiness stage (TRL>9)<
- **G.O.2.** The development of the AEMS logigram – by completing this objective the logical algorithm of the AEMS was developed, on which both the hardware and software designs were based,
- **G.O.3.** Identifying and selecting the relevant energy boundaries for the experimental development of the AEMS – this stage allowed for the identification of the optimal testing and validation conditions of the results which can be obtained by implementing the AEMS. It also led to the identification of the main future improvements of the proposed AEMS,
- **G.O.4.** The hardware and software development of the AEMS – by reaching this objective, the AEMS concept was materialized into a completely functional system, ready for the testing, validation, and optimization stage,
- **G.O.5.** Testing, validating, and optimizing the AEMS – the results obtained via the Case Studies presented in Chapter 4, by implementing various analysis modules in various types of energy boundary prove the viability and replicability of the designed system. Throughout the doctoral studies, an AEMS improvement stage

was also conducted, after testing its performance on a reference energy boundary, by implementing additional forecasting functionalities by considering an increased number of variable factors.

2. Relevant theoretical aspects

In order the develop the proposed AEMS and to reach G.O.1 and G.O.2, the first step practical step was to undergo an in-depth analysis of the existing EMS. To ensure an as high as possible replicability of the AEMS and a high performance, an in-depth analysis of the main EnPI was also conducted, with regard with the best practices indicated by the ISO 50001-50015 group of standards regarding the normalization of EnPIs with relevant variable factors.

An in-depth analysis of the mathematical models for determining the main PQIs was also conducted. These models were then adjusted and included in the monitoring and evaluation routines of the AEMS.

2.1. Energy Management Systems

In order to identify the opportunity of developing the AEMS and to determine the required functionalities and key attributes of it, an analysis of the main available EMS was conducted, by means of literature reviewing. A State-of-The-Art (**SOTA**) analysis was thus conducted.

To highlight the differences and the common aspects of the proposed methodology, a **SWOT** (Strength, Weakness, Opportunity and Threat) analysis was conducted for the SOTA technologies.

The main criteria used for the SWOT analysis consisted in:

- **INPUTS**: Are the Measures / Variables which are inputs in the EMS sufficient for a correct / complete quantification of the EnPI / PQI?
- **FUNCTIONS**: Is the EnPI / PQI quantification properly done?
- **FINAL OBJECTIVES**: Are the outputs of the EMS useful for increasing the EnPi / improving the PQI / maximizing the financial profitability of the Organization?

It was thus observed that neither of the SOTA technologies take into consideration the influence generated by the PQIs over the profitability of a power grid / microgrid. Also, in neither of the cases, the EnPIs are not normalized by considering relevant variable and static factors, even though in some of the systems a subtle correlation between EnPIs and variable factors (such as the average outdoor temperature) is done. The interdependency between the EnPIs and the PQIs is also not considered in neither of the analyzed systems.

It can be thus concluded that integrating the notion of normalizing and optimizing the interdependency between EnPI and PQI and developing an AEMS are novel and innovative aspects which can contribute to a significant increase in the profitability of the energy boundary in which the AMES would be installed.

Regarding the commercial ready EMS, it can be observed that these are custom-built for specific applications. The replicability of the available EMS to different types of energy boundaries is difficult. Also, these systems to not take the PQI evolution and impact into account when quantifying the EnPI.

Based on the SOTA / SWOT analysis, several critical points for AEMS to answer to were identified. The AEMS must be able to:

1. Monitor, in all relevant points, the values of the selected PQIs,

2. Quantify the energy performance and the financial impact of the PQIs,
3. Quantify the EnPIs instead of purely metering the energy flows, so that it can lead to a benchmarking potential and thus be used to establish reference levels for energy use,
4. Normalize EnPIs with respect to the critical variable factors,
5. Forecast the evolution of both energy demand and EnPIs, so that it can lead to a maximization of the energy market participation for the end-user,
6. Identify, propose, and quantify from both an energy and financial point of view EnPIAs and PQIIAs,
7. Identify, propose, and quantify form both an energy and financial point of view hybrid energy generation and storage projects, by using renewable energy sources available in the energy boundary site,
8. Provide the reporting and notification functionality for the end-user's personnel, differentiated based on the position it occupies in the company (technical / commercial / top management).

The main barriers in developing the AEMS, identified from the previously mentioned analysis are:

1. Potential difficulties in integrating existing monitoring systems from an energy boundary into AEMS (*low probability, as AEMS utilizes raw data from the monitoring systems, which can be transmitted through any type of communication protocol to the main Server*),
2. Potential difficulties in correctly identifying the critical variable factors for various energy uses (*the impact can be minimized by configuring the normalization system after installing the AEMS and after undergoing a preliminary measured data analysis and by installing variable factors monitoring / metering systems at a local level, when possible*),
3. Potential difficulties in integrating existing expert systems from the energy boundary into AEMS (*the impact can be minimized by introducing the relevant data by the AEMS operator, when installing / configuring the system*),

The risks which need to be minimized after the AEMS installation are:

1. Ensuring the cybersecurity of the AEMS (*can be done by implementing the AMES on-site, in a first stage and by using standardized communication protocols, secured by unique cryptographic keys*),
2. Ensuring the up time of the AEMS, regardless of the end-user status (*back-up power supplies will be installed in various relevant points, to ensure a redundancy for critical AEMS systems*),
3. Choosing a sampling frequency which will lead to maximum performances with a minimum computational resource (and, implicitly energy resources) use.

2.2. Energy Performance Evaluation

Implementing Energy Performance Improvement Actions at end-user level is one of the easiest ways to increase the overall energy performance to the goals and targets presented in Chapter 1. In the thesis most of the analyzed energy boundaries were tertiary energy sector end-users (office buildings, public buildings, commercial centers etc.).

Considering the main objective of developing an Advanced Energy Management System, the most relevant EnPIs were analyzed.

Based on these, several EnPIs were proposed for the analyzed energy boundaries on which AEMS was developed, tested, and improved.

To ensure an as high as possible quality of the energy analysis done by the AEMS and, implicitly, of the recommended EnPIAs proposed by the system operator, it is necessary to adapt the EnPI list on a case-by-case basis. The EnPI selection must minimally consider:

- The potential to monitor the energy flows which defined the proposed EnPI,
- The existence of variable factors dependency,
- The potential to monitor the variable factors,
- The existence of a potential for improvement of the process for which the EnPI is defined.

Based on these restrictions, the following EnPIs were selected:

- *Specific electricity use reported to the useful surface* – it helps the end-user to quantify the electricity use required for undergoing it's current activity for each square meter of useful surface,
- *Specific electricity use reported to the number of clients* – it helps the end-user to quantify the electricity use required for each client / person in the energy boundary,
- *Specific electricity use reported to earnings* – it helps the end-user to quantify the electricity use required for generating one thousand EUR of earnings,
- *Specific equivalent CO2 emissions reported to the number of clients* – it helps the end-user to quantify the sustainability of the energy boundary,
- *Specific equivalent CO2 emissions reported to earnings* – it is an indicator which offers an overall view of the environmental impact generated by the energy boundary for every one thousand EUR of earnings. This EnPI can be assimilated to a global environmental sustainability indicator,
- *Energy Intensity* – A global EnPI which enables the evaluation of the efficiency of energy resources use for the current activity of the company. It quantifies the overall energy use by reporting it to the total earnings generated by the base activity and it takes all forms of energy into account (electricity, thermal energy, natural gas, fossil fuels etc.).

The main variable factors considered in the development of the AEMS are the average outdoor temperature, relative humidity, rainfall, natural illumination level and the cloudiness level.

The next step is to define and quantify the static factors. A static factor is a parameter which does not vary over the analysis period, but which may become a relevant variable factor in the future, if the initial conditions change.

The analysis period is basically the period over which the initial value of an EnPI is compared with the new value, after the implementation of an EnPIA.

The importance of normalizing the EnPI values comes from the desire to obtain an as clear as possible image over the motives of its variation over time. When EnPIs vary form a reporting period to another and no static factors were changed, variable factors are always responsible for it.

It must be mentioned that some of the variable factors (such as the average outdoor temperature) are not influenceable by the end-user, the top management of the company or by the decision-making process. In this case, the variance of the independent variable factor must be accounted for and the target / expected EnPI values must be adjusted.

Normalized EnPI and the determined Energy Baseline will be used for quantifying the efforts of improving the overall energy performance of the organization.

An organization can decide to periodically reset the values of these two indicators, either because of a major change form the initial conditions (e.g: the fundamental change of the current activity, the change of the technology used in the manufacturing process, the movement of the production site in a new geographical area etc.) or from subjective reasons.

EnPI normalization can be done by using three distinct mathematical models: Regression, Lagrange interpolation and Neville's algorithm.

To choose the best suited normalization methodology for the development of AEMS, a comparative test of all three methods was conducted. The results of the simulations of a sample size of 121,232 data sets (with a dependent variable – electric power use and five predictive variables – the selected variable factors) are presented in **Table *2.2.1***.

Table 2.2.1 – Normalization analysis results

Mathematical model	Computation time	Standard deviation
SIMPLE LINEAR REGRESSION	00:00:05	13.341
MULTIPLE LINEAR REGRESSION	00:01:21	5.492
LAGRANGE INTERPOLATION	00:03:15	1.421
NEVILLE'S ALGORITHM	00:06:03	1.291

It can be observed that Lagrange Interpolation and Neville's algorithm lead to the smallest standard deviations. Even though Neville's algorithm led to a standard deviation 3.80% smaller than Lagrange interpolation, the computation time was higher by 91.4%. As such, for the analyzed energy boundaries the EnPI normalization will be done by applying Lagrange Interpolation, this method leading to the optimum between the computation time and the standard deviation of the results.

In order to increase the flexibility of the proposed solution, when configuring the AEMS and throughout it's operation, the mathematical method of normalizing the EnPIs can be changed, from a set of available functions, which can be continuously updated with new methods of normalization, based on ensuring the optimum ratio described beforehand.

For developing the technical, energy and financial performance analysis model, AEMS will require both energy related data (such as the power flow) and operational data (such as the state of various end-uses / receivers) and organizational data (productivity, earnings generated etc.).

At the same time, to maximize the efficiency of the EnPI normalization process, the frequency of data sampling and their quality must be high enough to ensure a minimum computation time and standard deviations. Otherwise, if the computation time passes the 15 minutes limit, the results provided by AEMS will have a significantly lower impact, especially because, starting form 01.02.2021, the metering period decreased from one hour to fifteen minutes – so AEMS will not be able to contribute to the optimization of the energy market participation of the end-user.

In order to integrate the capability to real-time determine the EnPI and normalize it and to determine the Energy Baseline with a high enough accuracy, the AEMS must be capable of:

- Monitoring, in real time, the evolution of the power demand on the energy boundaries on which the EnPIs are defined,
- Acquiring, from existing systems, relevant non-technical data, such as financial results (e.g.: earnings over a period of time),
- Monitoring, in real time, the variable factors which influence the analyzed EnPI,
- Forecasting (internally or by using software solutions or external databases) by using machine-learning algorithms, the evolution of external variable factors – such as meteorological factors,
- Forecasting by using machine learning algorithms the evolution of the analyzed EnPi by using variable factors forecasts, with a standard deviation of maximum 2%,
- Notifying and alarming the proper personnel when EnPI values are above the set threshold or above the forecasted values,

- Storing a high volume of raw data, required for the learning and testing stages of the machine learning algorithms.

2.3. Power Quality Indices Evaluation

One of the specific objectives of the thesis is to quantify the impact that poor PQIs generate on the EnPI and, implicitly, on the overall energy and financial performance of the analyzed energy boundary, on which AEMS will be deployed.

The PQIs can be classified based on the entity which is responsible with maintaining an admissible variation interval for them, or, when needed, with taking actions to improve them – PQIIA.

The PQIs are thus split into *primary power quality indices* – the DSO (Distribution System Operator) is responsible of maintaining their values and/or correcting them and *secondary power quality indices* – the end-user is responsible of maintaining their values and/or correcting them.

The *primary power quality indices* (PI) are those PQIs which describe the quality of the service / product – frequency, voltage amplitude, voltage sags and spikes.

The *secondary power quality indices* (SI) are those PQIs whose values are influenced / determined by the end-user, such as harmonic distortions, unbalances, and voltage fluctuations.

The following PQIs were selected and modeled into the proposed AEMS, based on their quantifiable impact on the EnPI:

a) Voltage Peak Factor (k_v) – defined as the ratio between the maximum value of the voltage curve and the RMS value (PI),
b) Voltage Form Factor (k_f) – (PI),
c) Voltage sags and short-term interrupts (PI),
a) Voltage spikes (PI),
b) Voltage unbalances (PI) – a simplified method of evaluation was used, in order to maximize the calculation process,
c) Current unbalances (SI),
d) PCC Power Factor (SI),
e) Voltage Total Harmonic Distortion (SI),
f) Current Total Harmonic Distortion (SI),

In order to integrate the capability of real-time determining and evaluation the PQI and the capacity to quantify the impact they generate on the EnPIs and the Energy Baseline, the AEMS must be capable of:

- Monitoring, in real time, the evolution of electrical measures, with a sampling ratio of at least 128 samples per cycle,
- Monitoring / determining the following (at minimum):
  - Half period values of line and phase voltages,
  - RMS values of line and phase voltages and electrical current intensity,
  - Electrical current and voltage harmonics, up to at least the 40^{th} rank (2 kHz),
  - Total Power Factor values, for each phase,
  - Electrical current intensity over the neutral wire, when the grid is configured as TN-S,
- Being installed in all relevant electrical nodes from the low-voltage grid of the end-users, regardless of the current intensity in that node (it must be compatible with various current measurement devices / systems – current transformers (ct), Rogowski coils, shunt resistors, Hall sensors),

Increased attention must be given to the effects generated by distorting regimes on the current measurement systems. If these are not properly sized or chosen, they can introduce massive errors in the system, thus significantly harming the accuracy and performance of the AEMS.

Because of this, all the current measurement systems used in the experimental development stage of the AEMS were Rogowski coils (IFA analyzer + Class A power quality analyzer) and Hall Sensors (SENSIX analyzer).

2.4. Digitalization of Energy Management Services

The AEMS must offer the potential of evaluating, over long periods of time, the evolution of the relative energy performance, in order to quantify and minimize the effects of the growing energy demand of the analyzed energy boundary – justified by the economic growth of the company, as a result of increasing the overall financial performance.

The fourth industrial revolution (*Industry 4.0*), also called the production based digital revolution, leads to the transformation of conventional manufacturing plants into smart factories, by using software solutions which allow for the integration and interconnection of the technological process and various systems used in it, by using IoT (Internet of Things) technologies and Big Data and Analytics concepts. Applying the concepts and principles of the fourth industrial revolution on the development of AEMS, by unifying the digital technologies with the conventional industry, leads to the creation of an integrated system made up from equipment, machinery, employees, mobile devices and IT&C systems which ultimately generates four main advantages:

- The optimization of the *time* resource: by automating and digitalizing, the data acquisition and process is autonomous, reducing the effort of the employees and freeing up additional time for them to turn to other value generating activities,
- The optimization of *costs*: the increase in data accuracy, the increase in various analysis accuracy and presenting the results in the proper format with regard to the reader's position in the company can lead to an improved planning of costs and earnings,
- Increasing the *flexibility*: the possibility of optimizing the processes based on data analysis provided by various energy / operational and financial flows significantly increases the global flexibility of the company,
- *Complete integration* potential: as the process is completely automatized and digitalized, the global up time increases.

3. Developing the Advanced Energy Management System

The study aimed, on the one hand, to carry out a detailed analysis of the various technical solutions to improve IPE and the impact they have on ICTEE, and on the other hand, the analysis of the impact of increasing the share of distributed sources of generation. of electricity from renewable sources has it on the two categories of indicators. The goal is to determine and develop an integrated, real-time analysis model to maximize the technical, energy and financial performance of the energy contours on which it is applied.

In this regard, several independent analysis modules have been developed, covering various areas, such as determining the Peak Shaving Potential (AGS), increasing energy and economic performance by reducing THD_I and using Machine Learning procedures to forecast both energy use and the evolution of EnPI and PQIs. The integration of the analysis modules in the AEMS was done starting from the logigram of AEMS, proposed in the thesis (see **Figure 3.1**).

The AEMS algorithm is based on a series of inputs, categorized as "Performance Criteria established by the Organization", of which the most important are: The period of technical, energy and economic analysis and Hierarchy of targets for the Top-Management: production, specific energy use, equivalent CO_2 emissions, power quality, operating costs, maintenance costs etc.

After setting these initial input data, which consider the view and goals of the company's Top Management, the measurement and verification protocol is defined, which operates within a logic loop. The predefined measurement interval, at the points where metering / measurement systems are installed, is one second, with an aggregation period of fifteen minutes, according to the provisions of IPMVP (International Measurement and Verification Protocol). This interval is also related to the methodology for calculating the Maximum Duration Load (MDL).

At the first initialization of the algorithm, the User must define the Economic Indicators (EI) - they can be taken from ERP (Enterprise Resource Planning), from the accounting management software or can be entered manually - of which the most important are: Monthly / Annual energy Costs, Acquisition costs of various equipment used in production / electrical receivers, Monthly / annual operating costs, Monthly / annual maintenance costs. The user must also define and enter the Technical Indicators (TI) - the technical characteristics of the equipment under monitoring / metering, which can automatically be acquired from the ERP or manually introduced by the system operator (TI's can be: Nominal power of the receiver, Daily duration of use of the receiver, Average daily load of the receiver etc).

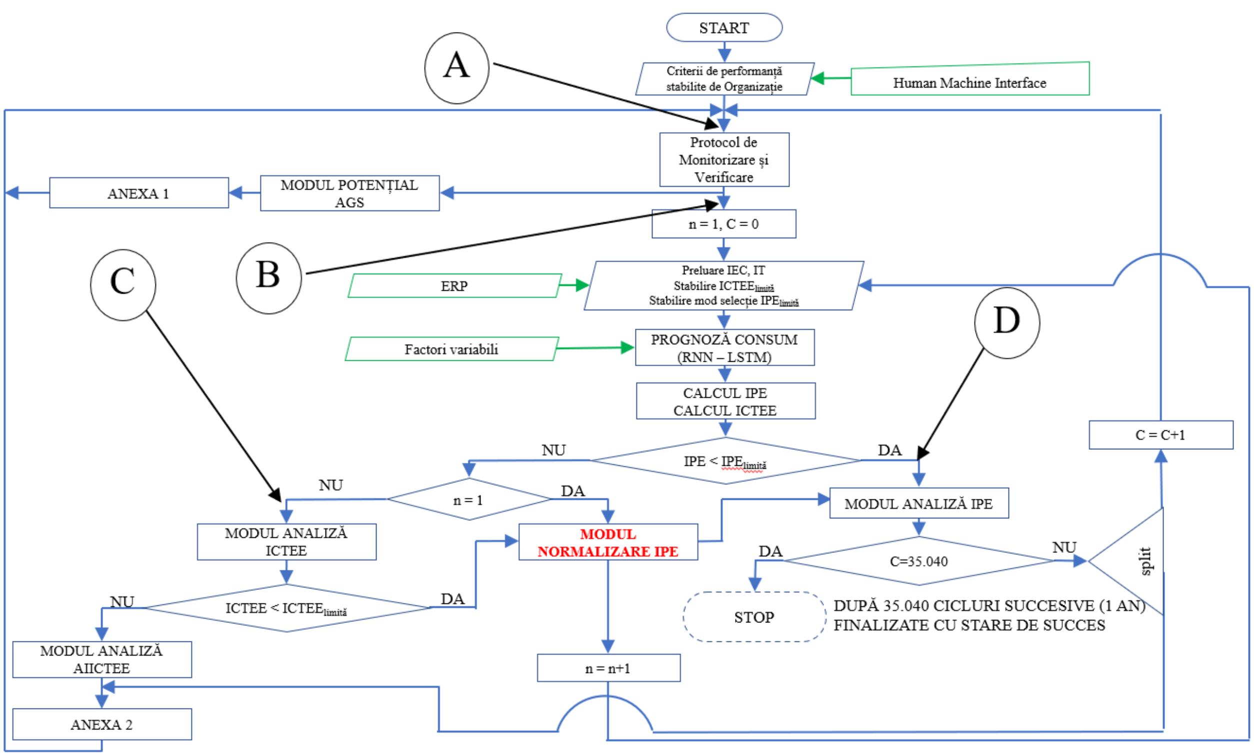


Figure 3.1 – AEMS Logigram

Once the monitoring loop has started, the algorithm will take over the values recorded by all metering / monitoring systems during the "Monitoring" stage, respecting the principle of simultaneity. The user will be able to select the EnPI evaluation method, choosing the way in which the IPE limit values will be determined or established. To cover all possible scenarios, the User will be able to choose between:

- Establishing the limit value of EnPI as an arithmetic mean ($EnPI_{lim} = EnPI_{av}$) for a chosen reporting period,
- Determining the limit value of IPE as absolute value ($EnPI_{lim}$=val), if there is the information needed to establish this value - method applicable if there are several similar energy boundaries, whose maximum EnPIs are known and all the values registered under a global value, established at Company level;
- Establishing the reporting value of IPE based on an algorithm specified in the regulations in force and agreed by the Beneficiary.

The values thus calculated are then compared with the reference values: EnPIs chosen by the User in the previous stage and predefined PQIs, according to the legislation, norms and technical standards in force. If the values fall within the set admissibility limits, a "Report" is generated, and the logic loop is resumed with the next set of measured values.

If the EnPI values do not fall within the established admissibility limits, the normalization of the EnPI depending on the External Variable Factors (EF) or Static Factors (SF) is done. If the standardized EnPI is still above the limit value of the reference EnPI, the verification of the PQIs compliance with the permissible limits established by the legislation, standards and technical rules in force will done. If the values of one or more PQI do not fall within the established admissibility limits, the impact that exceeding these limits generate on the analyzed IPEs is assessed.

Each PQI that has recorded values outside the established admissibility limits is quantified and a partial report is generated. This report presents the economic quantification of the impact of non-compliance with the cut-off value by the PQI concerned and how it influences the IPE values. All these partial reports are then incorporated in a "Final Report" which ends with a series of "Recommendations" in order to remedy the problems recorded for the User.

However, if the PQI values meet the established limits and the current values (EF_{act}) are compared with the values recorded in the previous reporting period ($EF_{previous}$) and the EF_{act} values do not differ by a relevant percentage for each of the analyzed factors, the cause of non-compliance is organizational. A report is thus generated and sent to the decision-makers on the operating side, for which a weekly report is prepared and sent through which the economic losses are quantified and cumulated.

3.1. Developing, implementing, and testing the monitoring system

Taking into account the aspects highlighted in the SWOT Analysis carried out in Chapter 2, and the relevant legislative aspects, the first stage of the research and experimental development of AEMS consisted in choosing the relevant energy boundaries.

In order to acquire the relevant energy data, several types of monitoring systems were used, which will be presented below.

Firstly, an advanced monitoring system developed by the Institute of Atomic Physics was installed and tested, in partnership with NET ENERGY S.R.L. - installed in 3 measurement points.

The system works as an IoT module, capable of connecting to the Internet an extensive class of local modules used for data acquisition. The Central Unit (CU) is configured to provide communication via the Phoenix bus within the DIN rail (between UC and auxiliary modules), two configurable serial channels (RS232 / RS485 or I2C) and GSM (signal transmitter + amplification antenna).

The CU measures the three alternating voltages (corresponding to the three phases).

The local modules ensure the acquisition of four analog signals (max. 500 mA) that measure, through Rogowski coils, the values of electric currents on the three phases and on the neutral conductor of the network with a resolution below 0.2%. Also, the phase shift between the electric current and voltage curves is measured, as well as the degree of harmonic deformation.

In the process of data acquisition 4 voltages (L1, L2, L3, N) and 4 electric currents (L1, L2, L3, N) are measured, with a number of 64 samples every 312.5 microseconds.

The local modules are equipped with two additional inputs, configurable as a Switch (SW) or serial channel inputs, but also with an optotriac that has externally connectable terminals and allows the transmission of any commands for remote control of switching equipment.

The installation phase of the systems was started in June 2020. The Central Units were constantly improved, through updates of the proprietary software developed in partnership with NET ENERGY S.R.L., reaching a stable version in September 2020. The measurements that were the basis for the elaboration of thesis were conducted between 06.09.2020 - 25.01.2021, with a measurement frequency of 1 data set / second and an aggregation of data measured in the CU at 1 minute. The database was subsequently completed with measurements conducted between 25.01.2021 - 28.02.2021.

The CU transmitted the data via GSM with an aggregation of 1 data set per minute for the entire duration of the measurements to the dedicated physical server, by using a Cloud Storage service.

Additionally, an advanced monitoring system developed by SENSIX S.R.L. was installed and tested (https://sensix.io/) - installed in a tertiary sector energy boundary. The Central Unit (CU) is configured to provide communication through two configurable serial channels RS232, RS485 or I2C for communication with its own peripherals or any other existing devices in the monitored structure and via Wi-Fi by a signal transmitter and an amplification antenna.

The CU measures the four alternating voltages (corresponding to the three phases and the neutral conductor) and the intensities of the electric currents on the three phases and on the neutral conductor, using either a set of Hall sensors or shunt resistors. The modules ensure the acquisition of four analog signals (max. 32 A), with a resolution below 0.3% but also the phase shift between the electric current and voltage curves and the degree of harmonic deformation.

In the process of data acquisition 4 voltages (L1, L2, L3, N) and 4 electric currents (L1, L2, L3, N) are measured, with a number of 64 samples every 312.5 microseconds.

In order to validate the data recorded by the two independently developed systems, six Clas A three-phase power quality analyzers were used, according to the in-force provisions.

Two Fluke 1770 three-phase mobile power quality analyzers were used, with the help of which electrical energy measurements were performed in parallel with the independently developed systems, to validate the accuracy of the data measured by them. The transmission of the measured data was done via ethernet, to the AEMS server. Also, for another energy boundary, four Janitza UMG 512 three-phase fixed power quality analyzers were used, which allow sampling at a rate of 25.6 kHz (512 samples over a cycle). For these, the retrieval and centralization of data in the AEMS Server was done using the Modbus protocol - TCP / IP.

In order to evaluate, with a high degree of accuracy, both the evolution of EnPIs and the evolution of PQIs, the proposed monitoring scheme is based on the FENCE Diagram presented in Chapter 2 of the PhD Thesis and takes into account the basic principle of PQI (classification of users according to ICTEE).

The first stage in the development of the software solution was the aggregation and statistical analysis of the measured data, in order to identify possible measurement errors, information transmission errors or exceptional situations, such as interruptions in the power supply of the analyzed energy boundary. The files containing the data recorded in Comma Separated Values (CSV) format - UC IFA / SENSIX or Excel - Fluke 1770, Janitza UMG 512 were processed and brought to the desired form and format, by building a conversion algorithm.

In situations where measurement errors have been recorded (most often due to communication / data conversion errors), in order to use the data recorded for the purpose of driving the neural network that will underlie the forecast of electricity consumption depending on variable factors, the regression method was used, which consists in replacing the erroneous values with the value of the indicator determined by calculating the 95th percentile.

To increase the efficiency of the data regeneration process, the proposed algorithm was applied directly to the raw values provided by the monitoring systems.

In order to assess the correctness of the measured values, the following logical process of data verification was established (see ***Figure 3.1.1***), as an integral part of the LOGIC BLOCK called MONITORING AND VERIFICATION PROTOCOL.

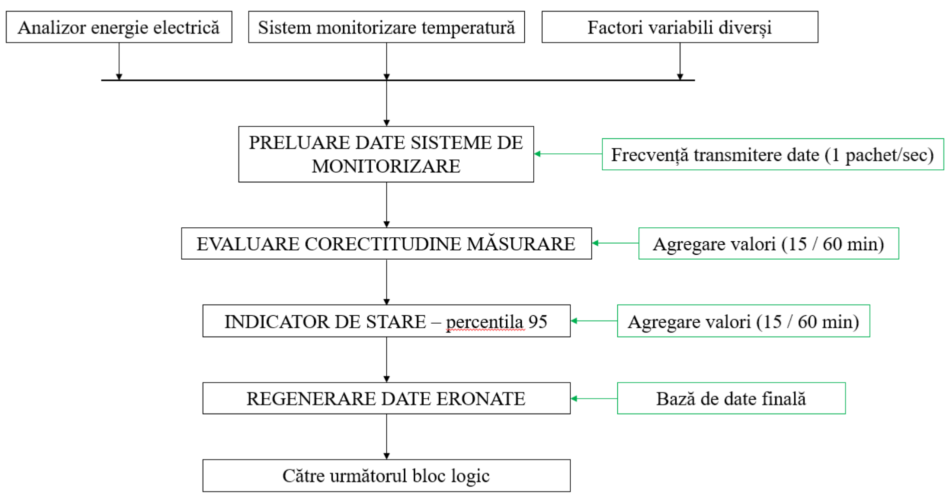


Figure 3.1.1 – Algoritm verificare corectitudine date măsurate

After acquiring the measured data from the existing / available systems, with a transmission frequency from the analyzers / monitoring systems to the server of 1 data packet / second, these data are used in the logical block to evaluate the correctness of the recorded values.

An aggregation of the measured values in sub-sets of 900 (900 seconds - 15 minutes) or 3,600 values (3,600 seconds - 1 hour) is performed, depending on the type of measured data. Statistical analysis applies to each such subset of records.

It was proposed to aggregate the recorded data in one hour sets to maintain the correlation with the variation of the external variable factors - at aggregation periods of less than one hour the factors variation is much too small to be able to train the Machine Learning algorithm with a high degree of confidence. At aggregation periods longer than one hour, the variation becomes too large and, implicitly, the accuracy of the electricity consumption forecast will be strongly influenced in a negative way.

In order to optimize the related storage space, the monitoring and verification logic block stores in the long term (more than one year) only those statistical data relevant to the end user - especially the results of technical, energy and financial analyses. Quantifiable energy data in monetary units (such as electricity consumption) is stored indefinitely, this process having a low memory requirement due to the small size of the data but also their frequency (a 15-minute record in the PCC).

For all voltage values, any deviation from the permissible range $V_C \pm 10\%$ is reported in the log, where V_C is the contracted supply voltage (declared). Normally, this is the rated voltage (V_n) of the network but following an agreement between the Distribution Operator and the end user, it may be different. In the case study presented, $V_C = V_N = 400$ V.
By integrating the two monitoring systems developed by IFA and SENSIX in the experimental part of the thesis, which are at the prototype stage, significant improvements were made, by testing and validating their functionality. Also, SENSIX has taken over and integrated in its own platform to be commercially launched a series of energy reporting elements developed in the thesis (such as statistical analysis of the evolution of electricity demand, calculation of the equivalent CO_2 footprint etc.).

3.2. Development, implementation, and testing of the Analysis Modules

The second step in the development of the AEMS, after the commissioning of the monitoring system in several energy boundaries, using several types of physical systems - three-phase class A quality analyzers, IFA analyzers and SENSIX analyzers (thus demonstrating the interconnection and integrability of the AEMS), consisted in the development, implementation and testing of analysis modules.

In order to develop the algorithm for evaluating the PQIs, the evaluations were performed using class A three-phase power quality analyzers (according to the IEC 61000-4-30 standard), which ensured a data flow with a frequency of 1 package of measurements per second, for a period of 12 months, in a number of six relevant Low Voltage (LV) measurement points:

A. 1 Measurement Point – Industrial End-User:
1. In the Point of Common Coupling – the secondary of the 20/0.4 kV power transformer which supplies approximatively 25% of the power demand of an industrial end-user,
2. On the power supply of a production section in which highly waveform distorting devices were identified.

B. 1 Measurement Point – Tertiary Sector End-User 1 (office building):
1. In the Point of Common Coupling – the secondary of the 20/0.4 kV power transformer which supplies the power for the building,
2. On the power supply of the HVAC (Heating, Ventilation and Air Conditioning) system.

C. 4 Measurement Points – Tertiary Sector End-User 2 (four office buildings):
1. In the Point of Common Coupling – the secondary of the 20/0.4 kV power transformers which supplies the power for the buildings,
2. On the power supply of the HVAC (Heating, Ventilation and Air Conditioning) systems.

Analysis modules for all the PQIs presented in Chapter 2 have been designed, developed, deployed, tested and validated.

The EnPI evaluation algorithm was developed in a stratified manner, practically implementing the calculation methodologies for each EnPI, so that at the AEMS level the relevant EnPI can be selected by the user, depending on the specifics of his activity. This ensures the highest possible modularity of the AEMS and high replicability in any other energy boundary.

All EnPIs presented in Chapter 2 of the Doctoral Thesis were implemented. For the testing and improvement stage of AEMS, EnPIs selected and presented in Chapter 2 were used.

In its entirety, AEMS was developed using the programming language Py (Python) and the code builder Jupyter Notebook, which allows the use of an agnostic language (Py, C ++, Java, etc.) thus ensuring the greatest possible compatibility with other software solutions further developed and thus allowing their unification into a unitary, final solution.

In order to analyze the interdependence relationship between EFs (External Variables) and EnPIs and to determine the forecast of the variation of $EnPI_n$ = f (EFs), a complex set of Machine Learning systems based on LSTM (Long Short Term Memory) RNNs will be applied, introduced by Hochreiter and Schimdhuber in 1997.

The RNN LSTM was initially developed for the forecast of active power demand based on a single external variable factor (average external temperature). The LSTM RNN parameterization thus developed was performed by successive iterations, aiming to identify the optimal values of the hyperparameters that would lead to the best form of the active power demand forecast.

It used the following key values:

- Length of learning sequence (time_steps): 24;
- Number of neurons per cell (LSTM_units): 192;
- Epochs (epochs): 20;
- Number of examples from a learning step (batch_size): 24;
- Training / learning weight (train_test_split): 0.15.

After identifying the hyperparameters that led to the maximum degree of accuracy of the LSTM RNN, the LSTM was extended from a known variable to five predicted variables (average outdoor temperature, insolation level, degree of cloudiness, relative humidity, and wind speed), the open-source platform https://openweathermap.org/ was used.

Through this extension, the degree of accuracy of the developed software model and the quality of the selected hyperparameters were analyzed when new variable factors appeared. Also, for the transposition in a real context, the forecast of the electricity use is made using meteorological forecasts - thus quantifying and evaluating the uncertainties introduced by the meteorological forecast errors. For this, based on a monthly subscription, a call function of an API (Application Programming Interface) has been developed that provides an hourly forecast for a period of two (2) days, for each call. This API allows the transmission of a maximum of 2,000 requests per day, which practically means that a subscription can provide the daily weather data needed for 2,000 separate locations where SAME is implemented. The returned results are then processed for integration into the database, by transforming them from the JSON format provided by the API, into a format compatible with the Machine Learning algorithm.

Unlike the results obtained in the preliminary stage of development of the LSTM RNN, the use of forecasted meteorological data increases the uncertainty of the algorithm for predicting the absorbed active power, from an initial value of 0.5 - 2% to a value of 1 - 12%, depending on the accuracy of the meteorological data (real vs. forecasted).

It is therefore shown that there is a direct dependence between the accuracy of the active power demand forecast and the accuracy of the meteorological data forecast for the time intervals on which the prediction is made.

Also, an extremely important influencing factor is the energy behavior of the consumer (consumer behavior[1]).

In order to normalize the EnPI, the following calculation subroutine will be followed:

- ✓ It is verified if $EnPI_n$ = y is a function of EFs = x by applying the vertical line method,
- ✓ If the condition is observed, it is verified if y = f (x) is a one-to-one function, by applying the horizontal line method,
- ✓ By applying the Lagrange interpolation methodology, the expected values of y for various values of x are determined,
- ✓ By implementing a Machine Learning system, the previously determined form of the function y = f (x) will be adjusted based on the data recorded by the Monitoring system.

Lagrange Interpolation was used as a normalization method, and it was observed that it provides a similar function (over 0.80% less accurate) to that provided by the Neville Algorithm, with a significantly shorter computation time (over 90% faster).

Linear regression leads to a high mean square error, with an average value of over 13%, due to the large number of dependent variables considered, and is therefore not recommended for EnPI normalization.

Thus, Energy Performance Indicators (determined for the energy sector in the tertiary sector - office building) are normalized in relation to five variables considered relevant (historical): average outdoor temperature, relative humidity, cloudiness, lighting and wind speed .

The determination of EnPI over relevant periods of time (week / month / year) by AEMS also allows their normalization by reference to the evolution of variables, which is a significant advantage for the User, as he can use AEMS results for reporting at both company level (setting internal targets on energy performance / environmental impact), as well as at the level of the Ministry of Energy - Directorate for Energy Efficiency (annual reports on energy performance - energy questionnaire submitted by the Energy Manager of the User).

The proposed logic diagram of the IPE analysis module is presented in ***Figure 3.2.1***.

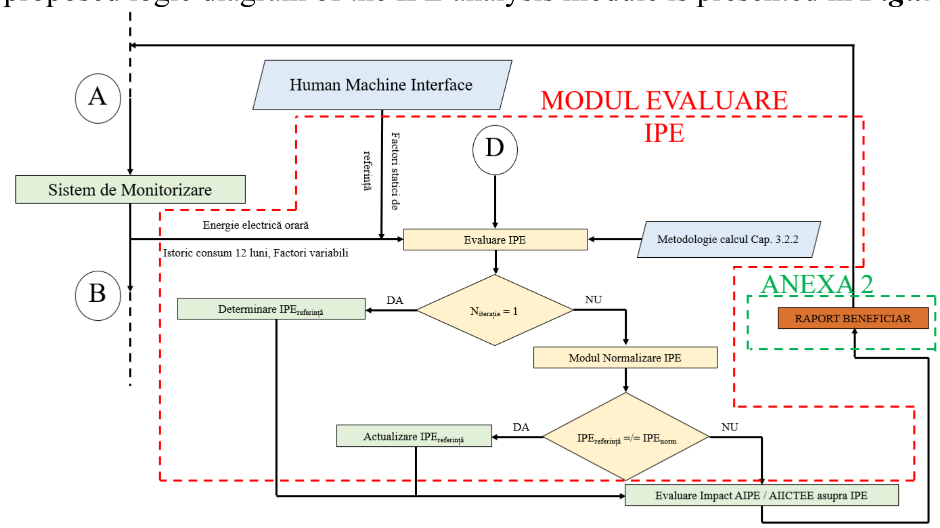


Figure 3.2.1 – Schema logică propusă pentru modulul de analiză, normalizare și predicție IPE

[1] *Consumer Behaviour* – Notion that takes into account the variability generated by the different behavior of users, depending on subjective or objective criteria, classifiable into categories such as: user behavior on weekdays / weekends / holidays, the behavior of users in a certain age group: 18 - 25 years, 26 - 40 years, 40 - 65 years, 65+ years etc.

The most cost-effective solution for decentralized power generation at the moment, at end-user level in Romania, is photoelectric technology, especially if it can be correlated with the potential for flattening the load graph and if its contribution to increasing continuity of supply is taken into account.

The peak of the daily load curve, although short in time, has a major impact on the energy and operational efficiency of electricity networks. The conventional approach to minimize the impact of this phenomenon is to increase electricity generation capacity during the peak period. However, this is not always economically feasible, can be inefficient in terms of generator use (as it involves having generators that need to be purchased, maintained, and used for only a few hours a day) and can significantly increase the specific environmental impact when peak sources use conventional fuels.

The four relevant strategies for Load Curve Flattening (LCF) and optimizing the operation of the electricity distribution network are:

1) Increasing the capacity of network elements by replacing power transformers and power lines with units of appropriate rated power (better optimized for the load curve), following techno-economic calculations;
2) Integration of Electricity Storage Systems (ESS);
3) Intelligent Integration of Electric Vehicles into Electric Grids (V2G - Vehicle to Grid);
4) Demand Response (DR).

One of the biggest challenges for the TSO is to ensure a balance between electricity generation and electricity demand, where an imbalance between these two components can lead to instability, voltage variations and even blackouts.

Imbalances between electricity generation and electricity demand result in extra demands on generating units and in low PQIs (frequency drops outside the permissible quality limits). The most effective solution to minimize these imbalances is to obtain a load curve with a low peak-to-peak difference.

Replacing power transformers and power lines is a very expensive operation and other solutions to increase the power transfer capacity are being sought. Also, obtaining permits and agreements for new power line routes and land for transformer stations is a difficult and lengthy process.

The load curve flattening factor is the most useful technique to quantify the variability of energy demand, thus determining how efficiently the asset under consideration is used. A low flattening factor implies highly variable load and inefficient asset utilization.

An optimal flattening factor is essential for the financial feasibility of power plants/power grids, leading to minimized energy costs. Improving the flattening factor is therefore mandatory to reduce the operating costs of power plants and power grids, thus increasing their economic and financial feasibility. Reducing the power demand at peak load is the simplest solution to improve the Flattening Factor.

Also, the transit of high peak power leads to increased, non-linear power and energy losses in transmission and distribution networks, according to the Joule-Lenz law.

In general, TSOs/DSOs and power generators do not own modern energy storage systems, which is why the electricity produced must not exceed the electricity demand, otherwise unit production costs increase significantly (for the same unit of energy - MW produced, sold and used, costs increase as more units of energy have been produced).

Reducing peak loads will lead to lower transmission and distribution costs by minimizing Joule-Lenz losses, increase equipment lifetime - by avoiding equipment operating at maximum/overloaded loads and minimizing maintenance costs, thus ensuring maximized financial benefits for the DSO.

Due to the intermittent nature of renewables, maintaining the stability and availability of power grids is becoming an increasingly important issue as the installed electrical capacity of these types of power plants increases.

Increasing the number and power of renewable energy power plants installed at end-user level (self-consumption regime) generates a number of significant benefits both at the end-user level (by avoiding a share of the cost of electricity purchased from the NES, relieving grid elements owned by the end-user - power transformers and power lines) and at the DSO level, by ensuring a better voltage level along the electricity distribution grid and relieving grid elements (power transformers and power lines) of load beyond economic operating limits.

At the same time, the increased implementation of distributed generation projects will, over time, lead to a reduction in the revenues of the DSOs/TSOs by reducing the level of energy transited through the networks owned/leased and operated by them, the economic effect being of a dual nature.

Increasing the number and power of renewables-based plants, combined with the use of ESS, can solve most of the usual problems caused by the load chart, through LCF. Also, the intelligent coupling of ESS with RES can eliminate or minimize the problems caused by the variability of electricity generation by RES, by minimizing the Balancing Market charges, by increasing the accuracy of the forecast of the amount of electricity absorbed from/injected into the NES.

Meeting a time-varying peak load is sometimes a process with extremely low financial efficiency and high environmental impact. Thus, the price of electricity generation increases during peak load, which is borne by end-users.

LCF is therefore also an important method for this category of market participants as, by approaching a differentiated tariff scheme, they can achieve significant savings on their energy bills by moving their own peak load to off-peak periods of the load curve at NES level.

Secondary benefits from AGS can be in increasing the reliability of end-user owned network elements, but also in improving the PQIs. Operating with below normalized/optimal load is not economic, as the transfer capacity for which the network element has been sized is not used rationally.

Using network elements (power transformers and power lines) at technically and economically optimal loads ensures that their lifetime does not fall below their normal service life as a result of avoiding overheating and insulation damage. Also, the introduction of a distributed energy source makes it easier to ensure the desired values of some PQI, the most relevant of which is voltage variation.

The technical and economic viability of applying the LCF procedure using Battery Energy Storage System (BESS) type ESS at the level of energy end-users was also analyzed in the thesis, as well as the influences of the development of RES and the impact of minimizing THD_I on their energy and financial performance.

The operating principle is to use BESS for LCF by charging the system during off-load periods and discharging it during peak load periods.

The use of BESS for LCF has been intensively researched recently by the international scientific community. All studies have shown that without the existence of an hourly differentiated pricing scheme (off-peak/peak), the exclusive use of BESS cannot be financially feasible under current market conditions.

A RES generator equipped with BESS can, however, have important advantages when bidding for bilateral contracts in the market where it can offer quasi-constant generation over time and avoid losses in case of forecast errors in electricity generation.

In this respect, the author analyzed the financial viability of a hybrid system for LCF, which will use both a distributed energy source in the form of a small to medium sized photoelectric power plant and a small BESS for electricity storage and LCF realization. The aim is to assess the financial potential of LCF procedures under current market conditions and to identify those adjustments that, once made, can lead to financial support for these types of actions.

As the aim of the AEMS is to increase energy, operational and financial efficiency primarily at the end-user level, an analysis module has been developed that will work under the assumption that the investment is made exclusively from the end-user's own funds, without any contribution, co-financing or support from the Distribution System Operator, although both the benefits and disadvantages of this solution will be passed on to the DSO, as explained in the previous chapters.

Implementation of LCF based solely on Peak-Shaving / Peak-Shifting procedures are financially feasible either if the range of variation of the electricity price is complex, taking into account peaks / gaps in the load curve, or if they actively participate in the electricity market by contracting on settlement intervals for the amount of energy needed.

Under these conditions, for the development of the theoretical model and the experimental procedure, a power contour fed through a power transformer having 20/0.4 kV with a rated power of 250 kVA, ONAN cooled, with $\Delta P_0 = 0{,}3$ kW and $\Delta P_k = 3{,}25\ kW$. The schematic diagram of the analyzed energy boundary is shown in ***Figure 3.2.2***.

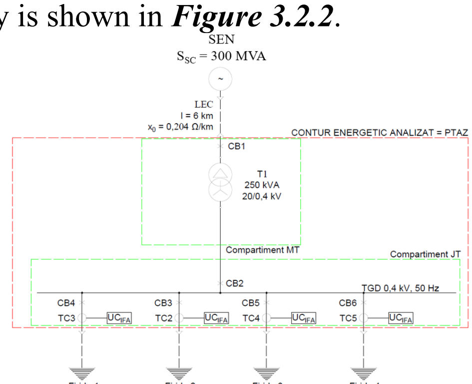


Figure 3.2.2 – Schema electrică monofilară de principiu a Postului de Transformare analizat

An optimum load factor of the power transformer leading to operation at maximum efficiency, β_{opt}=60 [%], as specified in the Regulation on the Technical Operation of Electrical Equipment in Primary Distribution, was considered, with oil-insulated, natural circulation and air-cooled, natural circulation (ONAN = Oil Natural Air Natural).

Depending on the technology used to manufacture power transformers, the optimum transformer load factor for maximum efficiency operation will be different. Within the developed software solution, the user will be able to select from a list the type of power transformer under consideration or manually enter the value of the optimum load factor for maximum efficiency operation.

In order to increase the energy performance of the power distribution process in the analyzed energy boundary, three variants are available:

1. Adoption of EnPIAs through which a decrease in the power flowing through the power transformer is achieved,
2. Replacing the existing power transformer with a correctly sized one to ensure operation at optimum load for as long as possible (requires a technical-economic calculation justifying the savings made compared to the investment required),
3. Implementation of both solutions presented above.

The next step was to determine the average daily load graph for the two types of days: working vs. non-working. By calculating the average values of the absorbed electric powers (mean) and aggregating the values thus obtained, the corresponding load graphs were constructed.

In order to determine the amounts of power above and below the optimal transformer load, respectively, a "0-crossing of the curve" sub-module was developed, which takes the optimal transformer load as relative zero.

This module determines with a deviation of 0.5% the moment of intersection between the load curve and the optimal load curve and then, by integration, determines the quantities of electricity in the analyzed interval - between two successive intersections. The results of this calculation are shown in ***Figure 3.2.3***.

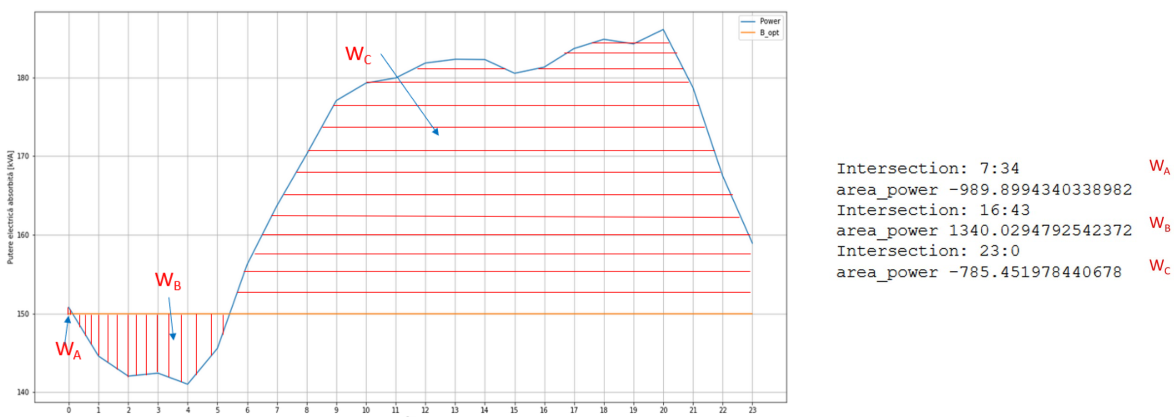


Figure 3.2.3 – Cuantificarea cantităților de energie din regimurile de gol / vârf ale curbei de încărcare, în cazul unui transformator cu puterea nominală de 250 kVA

It can be seen that in the case study presented, the areas identified by W_A and W_C represent overload operating ranges, and the area identified by W_B represents an underload operating range.

From the point of view of the distribution of operating regimes, it is found that in the analyzed case study, the power transformer load curve is characterized by a ratio of 14.5 to 1 in terms of the amount of energy absorbed in the overload versus underload regime.

Quantifying by operating times, it is observed that the transformer operates in overload mode (the load transited is higher than the optimal load) 18.5 hours/day and in underload mode only 5.5 hours/day.

It is worth noting that the shape of the load graph is different from the usual load graph, and a peak load operating regime is identified that spans several hours of the day. The main reason for this regime is the behavioral changes of users due to the COVID-19 pandemic - telework. This new concept generates a substantial change in the daily load curve at power transformers supplying residential and commercial users.

Therefore, knowing the quantities of energy related to the "overloaded" and "underloaded" regimes, a software module was developed to size and technically quantify an optimal Load Curve Flattening (LCF) solution.

In this respect, three technically feasible directions can be investigated:

- Implementation of Energy Performance Improvement Actions(*),
- Use of energy from renewable sources - photoelectric systems,
- The use of electricity storage solutions - batteries.

(*) *This point cannot be analyzed in the case of residential users, as it is difficult to quantify how to support the implementation of EnPIAs in households. It can only be quantified for industrial, tertiary-commercial and tertiary-institutional end-users.*

An iterative calculation model based on the PV GIS platform SARAH was developed for the sizing of a photoelectric power plant. Using the API made available by the aforementioned platform, the iterative calculation model tests the viability of installing a photoelectric system using the relation: $\mathrm{P_{1h,PV}} \leq S_{nT} \cdot cos\,\varphi_n + PV_{LC}$ [kW], where: $P_{1h,PV}$ $[kW]$is the maximum power produced by the photoelectric system, PV_{LC} [kW] is the maximum power absorbed at peak load, S_{nT} $[kVA]$ is the rated power of the transformer and $\cos\varphi_n = 0{,}90[-]$ is the neutral power factor.

The iterative calculation module calls the API in successive iterations (24 iterations per second) to determine the output of a photoelectric system using monocrystalline panels, with an average tilt of 30 degrees, without tracking system, based on the GPS coordinates of the analyzed site. The minimum installed power of the modelled PV system is 50 kWp (kW peak - power at peak production, under Standard Test Conditions - STC), and the upper limit is 1,000 kWp, with an iteration step of 1 kWp. For the example analyzed, the optimal installed power of the photoelectric system was determined to be 432 kWp.

Once the optimal installed power is determined, the software module simulates an optimal day of operation of the photoelectric system and plots, by overlapping, the power production curve.

By applying the "0-crossing of the curve" analysis sub-module, which takes the optimal load for maximum efficiency operation of the transformer as relative zero, the quantities of energy related to the photoelectric system below the transformer optimum (negative sign) and above the transformer optimum (positive sign) are determined - see also ***Figure 3.2.4***:

- The amounts of electricity produced by the photoelectric system below the transformer optimum (negative sign) represent a surplus that cannot be used as such for LCF;
- Quantities of electricity produced by the photoelectric system above the transformer optimum (positive sign) represent a surplus that can be used as such for LCF, if they overlap the (positive) quantities of electricity on the load curve.

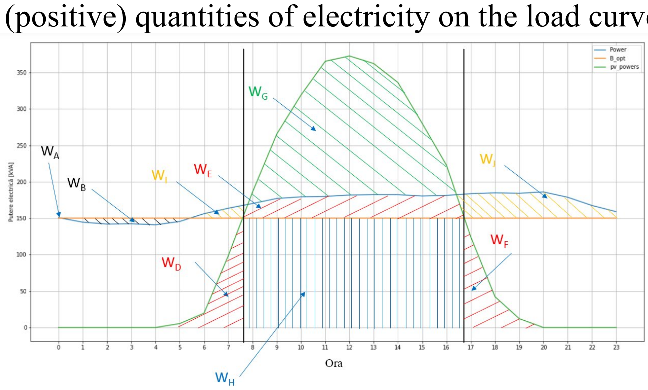


Figure 3.2.4 – Determinarea cantităților de energie electrică utilizabile pentru Aplatizarea Graficului de Sarcină (verde) și disponibilă pentru aplatizarea indirectă a graficului de sarcină (roșu și albastru).

The results provided by the module are presented in **Figure 3.2.5**.

```
--------------------------------------------------------------------------------
Interpretare rezultate
--------------------------------------------------------------------------------
Cantitatea de energie electrică produsă de sistemul PV: 3012.163 [kWh/zi]
Producția de energie electrică disponibilă pentru încărcarea sistemului de stocare: 2681.087 [kWh/zi]
Cantitatea de energie electrică necesară a fi acoperită de sistemul de stocare: 114.143 [kWh/zi]
Cantitatea de energie electrică disponibilă pentru încărcarea sistemului de stocare la încărcări sub-optime: 32.752
[kWh/zi]
```

Figure 3.2.5 – Rezultatele modului de analiză a potențialului de aplatizare a curbei de sarcină a sistemului fotoelectric

Since it can be seen that the photoelectric system is not able to ensure a correct flattening of the load curve if analyzed individually, an additional analysis module has been developed, dimensioning a BESS solution that has the role of optimizing the distribution of the electrical energy produced by the photoelectric system over a day, so that the flattening of the load graph is achieved at optimal parameters. To this end, a preliminary database has been designed, containing different types of battery technologies, technical characteristics, and financial characteristics.

The analysis module iteratively goes through all the entries in the provided database and determines what is the cost associated with each battery type in the analyzed regime. Based on these results, it applies a minimum function and displays the financially optimal BESS structure to the user.

Once the two systems (photoelectric and BESS) are sized, SAME continues with a techno-economic analysis module. The techno-economic analysis module uses the financial indicators presented in **Table 3.2.1**. In order to perform the techno-economic analysis, a number of user-defined inputs were considered, such as electricity price, electricity price growth rate, discount rate, analysis duration, specific cost of the photoelectric system and specific operating cost of the photoelectric/BESS system.

Table 3.2.1 – Financial Indicators used for LCF module

Financial Indicators			
Indicator	Notation	Formula	M.U.
Net Present Value	NPV	$NPV = \sum_{t=1}^{tst} \frac{I_t - C_t}{(1+a)^t} - CAPEX$	[EUR]
Internal Rate of Return	IRR	$NPV = \sum_{t=1}^{tst} \frac{I_t - C_t}{(1+IRR)^t} = 0$	[%/year]
Simple Payback Period	SPP	$SPP = \frac{CAPEX}{\frac{\sum_{i=1}^{tst} I_i - C_i}{t_{st}}}$	[years]

In order to determine the annual benefits generated by the project, the power and energy losses in the transformer due to operation at less-than-optimal load were determined to establish the baseline level.

Subsequently, power and energy losses were determined in the scenario of the implementation of the load curve flattening project considering the two components: the Photoelectric System and the Electricity Storage System.

The daily amount of energy required to pass through the transformer for it to operate at optimal load was also determined.

In order to increase the accuracy of the proposed analysis method, the developed software module also takes into account the following technical-economic aspects:

- The degradation over time of the photoelectric modules and the storage capacity of the electrochemical batteries, considering an average degradation/denomination rates of 0.6%/year for the photoelectric system and 0.01%/cycle for the storage system.

- The electricity price evolution forecast, using a WEB-CRAWLER application that evaluates (daily) OPCOM price reports on the various energy markets of interest (DAM, Intra-day and Balancing Market).

The results of the financial analysis module are presented in **Figure 3.2.6**.

```
Se propune instalarea unui sistem PV cu o putere instalată de: 432 [kWp]
susţinută de un sistem de stocare a energiei electrice bazat pe acumulatori având următoarele caracteristici:
                                  8
Tip acumulator               Li-NMC
DOD [%]                        80.0
Durata de viata [cicluri]    5000.0
Tensiune Nominala [V]        1500.0
Capacitate [Ah]               644.0
C-rate [-]                       C5
Curent nominal [A]            800.0
Incarcare [h]                   3.0
Energie disponibila [kWh]    1100.0
Pret [EUR]                 385000.0
Numar Acumulatori Necesar       3.0
Cost total BESS           1155000.0
------------------------------------------------------------------------------------------------------------
------------------------------------------------------------------------------------------------------------
CAPEX Soluţie: 1479000.0 [EUR]
OPPEX Soluţie: 49837.44 [EUR/an]
------------------------------------------------------------------------------------------------------------
------------------------------------------------------------------------------------------------------------
Energia zilnică tranzitată prin transformator - situaţia actuală: 4045.22 [kWh/zi]
Energia zilnică tranzitată prin transformator - situaţia optimă: 3600.0 [kWh/zi]
Energia zilnică tranzitată prin transformator - situaţia propusă: 1033.06 [kWh/zi]
Abaterea procentuală de la optim în situaţia propusă este de: 71.3 [%]
------------------------------------------------------------------------------------------------------------
------------------------------------------------------------------------------------------------------------
Pierderile de energie anuale prin transformator - situaţia actuală 16.71 [MWh/an]
Pierderile de energie anuale prin transformator - situaţia propusă 2.63 [MWh/an]
------------------------------------------------------------------------------------------------------------
------------------------------------------------------------------------------------------------------------
Economie de energie ca urmare a aplatizării curbei de sarcină:
14.08 [MWh/an]
------------------------------------------------------------------------------------------------------------
Economie medie anuală de energie ca urmare a instalării sistemului hibrid PV+BESS:
1023.8 [MWh/an]
------------------------------------------------------------------------------------------------------------
------------------------------------------------------------------------------------------------------------
Rezultatele analizei tehnico-economice:
Beneficiile medii anuale generate de instalarea sistemului hibrid sunt de: 327998.91 [EUR/an]
Durata de analiză a proiectului este de: 25 [ani]
Rata de actualizare considerată este de: 11 [%/an]
Venitul Net Actualizat generat de proiect este de: 319356.53 [EUR]
Rata Internă a Rentabilităţii aferentă proiectului este de: 13.22 [%/an]
Perioada Brută de Recuperare a Investiţiei este de: 5.32 [ani]
------------------------------------------------------------------------------------------------------------
------------------------------------------------------------------------------------------------------------
```

Figure 3.2.6 – LCF module – financial analysis results

It can therefore be seen that the project is only marginally viable in this case. There are several justifications for this, the most important of which are:

- The non-existence of an advantageous tariff system for Peak Shaving / Peak Shifting projects, which would imply differentiation of the electricity tariff according to the time of day; However, the implementation of a hybrid solution can generate financial advantages by optimizing participation in the energy market (given the quasi-constancy of the load schedule), harnessing excess energy through accumulation in the storage system, and avoiding penalties for failure to meet contractual conditions in the absence of solar radiation during the day (production forecast errors),
- Alignment of the load graph - load regimes above the transformer optimum are more than 4 times longer in time than load regimes below the optimum for full transformer efficiency operation, so the project cannot be implemented using BESS alone, without generating additional renewable electricity,
- Relatively high costs associated with operating/maintaining/replacing battery packs - given sustained technological progress, these are expected to fall in line with photoelectric technology.
- Flattening factor (pre-project implementation) and non-uniformity factor (pre-project implementation) were not within the range identified as attractive for such projects (0.4-0.6).

In order to accurately quantify the variability of the PV system output proposed for analysis, an ML-LSTM algorithm was developed which, based on historical consumption data and electricity production forecast (hourly data), determines the annual amount of electricity that can be covered by the implementation of the PV+BESS system, thus increasing the accuracy and precision of the techno-economic analysis module.

The logical diagram of the LCF module is presented in ***Figure 3.2.7***.

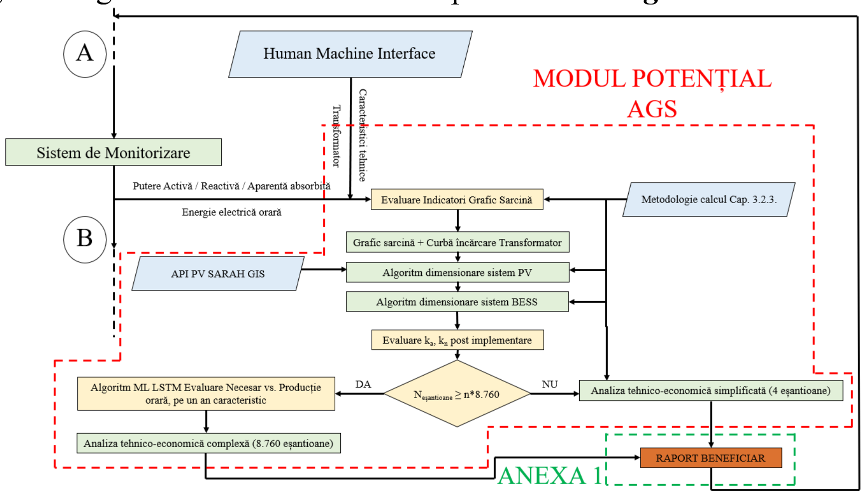


Figure 3.2.7 – Logic diagram for the proposed LCF module

According to the current technical standards governing the PQI analysis, the first step is always to check the Total Harmonic Voltage Distortion Factor. If the values recorded by THD_V are within the required limits, the analysis can continue with the investigation of the values recorded by the Total Harmonic Current Distortion Factor - THD_I.

The operation of distribution networks in distorted - harmonic current distortion - regimes leads to increased power and energy losses and operational and operational problems. The inclusion of PQI in the admissibility range is a necessity for optimizing the energy performance of electricity networks, whether in the residential, tertiary or industrial sector.

The operation of power grids with low energy performance negatively influences the potential application of the LCF procedures described above. Also, the presence of distorted waveforms can lead to the phenomenon of derating of power transformers.

Increased active power losses result in higher winding temperature during operation, which can lead to a corresponding reduction in transformer lifetime. In order to eliminate this, it is necessary to reduce the transformer load, i.e. use at a lower power than rated (denominating / de-energizing the transformer).

In order to provide additional functionality to the analysis module, an algorithm has also been developed to financially evaluate the potential obtained by limiting the THD_I, based on the Simple Payback Period limit considered acceptable by the end user. In this context, the default value limit is 5 years, but this can be replaced at any time by a value entered by the user via the Human Machine Interface (HMI).

It should be taken into account that the SPP limit value depends on the following factors:

1. The size of the investment (tens, hundreds of thousands, millions of EUR),
2. Financial strength of the company (turnover),
3. Type of investment (technological process, non-technological processes, organizational processes),
4. Cash Flow of the company,

5. Credibility of the company with (bank) financing institutions,
6. Existence and quality of the business plan related to the investment.

Thus, the usual values of the SPP limit are 3, 5 and 10 years respectively.

The financial analysis module determines the maximum amount of CAPEX (Capital Expenditures) that can lead, by minimizing the harmonic ranks identified as having values significantly above the recommended limit of 5% of the fundamental, to the recovery of the investment within 5 calendar years. Subsequently, the analysis module determines the Net Present Income that can be obtained over the 10-year study period, in accordance with the regulations in force, thus encouraging the end-user's representatives to take the decision to make the proposed investment.

The proposed logic diagram of the PQIIA implementation potential analysis module on minimizing the electric current distorting regime is shown in ***Figure 3.2.8***.

In order to support end-users, a module has also been developed to monitor in real time the evolution of the average power factor achieved at the level of the analyzed energy boundary (at the PCC level) and to quantify the costs of the reactive electricity (the decision to monitor the power factor at the user is determined more by its economic-financial impact and less by whether it is within the limit set by the neutral power factor).

A notification module has also been implemented, whereby the user's technical representative is notified in real time when the aggregated 60-minute average realized power factor is less than 0.65.

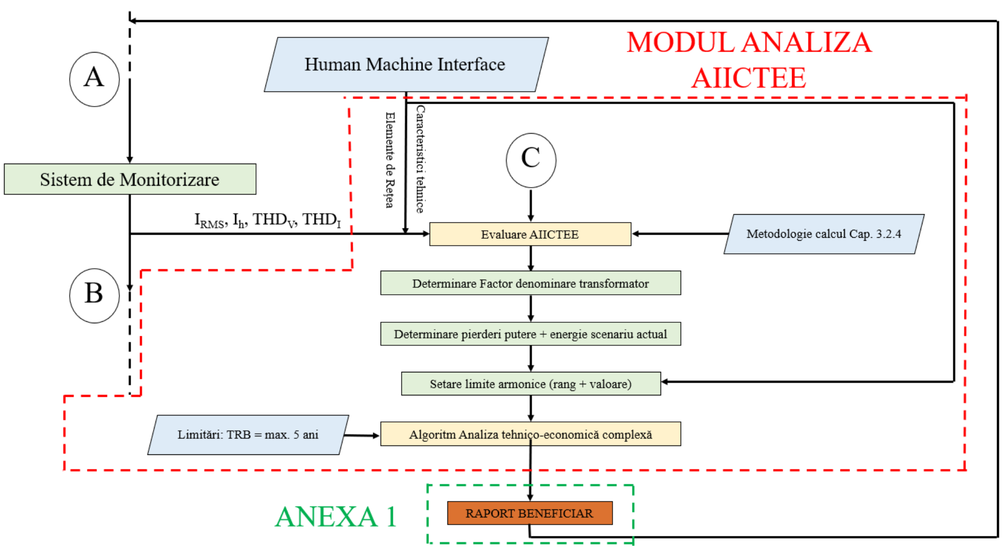


Figure 3.2.8 – Logic diagram of the PQIIA module - THD_I

3.3. Integrating the analysis modules in the AEMS

Throughout the thesis, a number of energy and financial analysis modules were developed, implemented, tested and validated, based on the main logigram of the AEMS:

A. **PQI Analysis module**, which evaluates, in real time:
   - Voltage sags,
   - Voltage spikes,
   - Interrupts,
   - Voltage Peak Factor,

- o Voltage Form Factor,
- o Voltage Unbalances,
- o Current Unbalances,
- o Voltage Total Harmonic Distortion,
- o Current Total Harmonic Distortion,
- o Total Power Factor (and, implicitly all active, reactive and apparent powers),
- o The cost of operating the energy boundary in non-neutral Power Factor regimes.

B. **The LCF Module**, which:
- o Evaluates, in real time, the load of power transformers,
- o Evaluates the power and energy losses in power transformers,
- o Quantifies the energy flows in under-loaded and over-loaded regime with respect to the optimal load of the power transformer,
- o Sizes, by using a dedicated API, a distributed energy generation system capable of providing the required power for the end-user in order to minimize the load transited through the power transformer (at the PCC),
- o Sizes a BESS system, capable of optimally distributing the RES generated energy in time, so that it ensures an optimal load of the power transformer,
- o Quantifies the financial benefit by doing an in-depth techno-economical analysis regarding the feasibility of the LCF project for the analyzed energy boundary.

C. **The PQIIA Module** – current harmonic distortion, which:
- o Evaluates the Total Harmonic Distortion Factor (THD_I) at the monitoring point / energy boundary level, in real time,
- o Determines the power and energy losses in the network elements (electric lines and power transformers) when operating in distorting current regimes,
- o Sizes a harmonic filtering system (based on the relevant harmonic ranks – such as 5, 7 and 11 but also 2n+1 rank),
- o Does a detailed techno-economical analysis through which it indicates the energy, financial and operational benefits which can be obtained by implementing the PQIIA and indicates the maximum CAPEX value for which the project is still feasible from a financial point of view.

D. **The EnPI Analysis Module**, which:
- o Evaluates, in real time, the evolution of EnPI,
- o Evaluates the evolution of aggregated (with an aggregation period set by the user) EnPIs,
- o Normalizes the EnPI with respect to the relevant variable or static factors, thus increasing the accuracy of the overall evaluation process.

E. **The Power Demand Forecast Module (PDF)**, based on the ML algorithm presented in Chapter 3, which:
- o Forecasts the power demand of the energy boundary, in three different stages of aggregation,
- o Forecasts the evolution of the selected EnPIs, in two stages of aggregation (hourly and daily).

As each module contains a technical component and a financial component, it is necessary to integrate the results provided by these modules into an overall financial function, providing an overview of the financial profitability associated with the use of electricity and, therefore, the potential for improvement/maximization.

This integration will also provide an overview of the potential for reducing environmental impact at the level of the analyzed energy boundary, by implementing the different actions recommended by AEMS.

Based on the description of the analysis modules in this chapter, the main financial results provided by AEMS will be presented in **Table 3.3.1**.

In **Table** *3.3.2*, the functions defining the financial indicators are presented, and Annex 5 details/describes their variables.

All the results provided by AEMS, for each Module described, have been integrated into the Human Machine Interface, in order to provide relevant, global results / reports that can give an overview of the potential electricity savings (and therefore the associated cost savings and environmental impact reduction).

Table 3.3.1 – Financial results supplied by AEMS

MODULE	RESULT	TYPE
A	Active Energy Cost – C_{W_P}	Periodic COST
	Reactive Energy Cost – C_{W_Q}	Periodic COST
B	Yearly Energy Losses Cost – Power Transformer Load – $C_{\Delta W_P}^{AGS}$	Periodic COST
	Cost of implementing the DER project – C_{SGD}	Investment COST
	Cost of implementing the BESS project – C_{SSEE}	Investment COST
	Yearly Energy Losses Cost Reduction – Power Transformer Load – $E_{\Delta W_P}$	Potential SAVINGS
C	Yearly Energy Losses Cost – High THD_I – $C_{\Delta W_P}^{THD_I}$	Periodic COST
	Yearly Energy Losses Cost Reduction – Low THD_I – $E_{\Delta W_P}^{THD_I}$	Potential SAVINGS
	Cost of implementing the Active Harmonic Filter – Maximum Cost – $C_{AHF,max}^{THD_I}$	Investment COST
D	-	-
E	-	-
TOTAL	Total potential Saving – E_{totale}	Potential SAVINGS

Table 3.3.2 – Financial Indicators – formulas and relevant variables

INDICATOR	FUNCȚIA	U.M.
$C_{W_P}^{initial}$	$C_{W_P}^{initial} = P \cdot t \cdot c_w = f\left(C_{\Delta W_P}^{AGS}, C_{\Delta W_P}^{THD_I}, P, PF, k_n, c_w\right)$	$[\frac{EUR}{time\ unit}]$
C_{W_Q}	$C_{W_Q} = P \cdot \sin(\mathrm{acos}(PF)) \cdot t \cdot c_{q_{paliere(PF)}} = f\left(P, PF, c_{q_{paliere(PF)}}\right)$	$[\frac{EUR}{time\ unit}]$
$C_{\Delta W_P}^{AGS}$	$C_{\Delta W_P}^{AGS} = \Delta P_0 \cdot t_1 \cdot c_w + \Delta P_k \cdot \left(\frac{W(t)}{P_M} \cdot \frac{\frac{W(t)}{P_M} + 10.000}{27.500 - \frac{W(t)}{P_M}}\right) \cdot \left(\frac{P_M \cdot PF_M}{S_{nT}}\right)^2 \cdot c_w = f(\Delta P_0, \Delta P_k, P_M, PF_M, c_w)$	$[\frac{EUR}{time\ unit}]$
C_{SGD}	$C_{SGD} = P_{rated,PV} \cdot c_{sp} = f\left(P_{Max_{PV}} = P_M(t), c_{sp}\right)$	[EUR]
C_{SSEE}	$C_{SSEE} = \left(W_{peste\ optim}^{fără\ PV} - W_{PV\ peste\ optim}^{cu\ PV}\right) \cdot c_{BESS} = \sum_{i=0}^{23}\left[\left(P_{i,med} - P_{opt}\right) - \left(P_{i,PV} - P_{opt}\right)\right] \cdot t_i \cdot c_{BESS} = f(P_{măsurat}, P_{opt}, c_{BESS})$	[EUR]
$E_{\Delta W_P}$	$E_{\Delta W_P} = C_{\Delta W_P}^{AGS} - C_{\Delta W_P}^{AGS,cu\ PV+BESS} = f\left(P_{măsurat}, P_{opt}\right)$	$[\frac{EUR}{time\ unit}]$
$C_{\Delta W_P}^{THD_I}$	$C_{\Delta W_P}^{THD_I} = \left(\Delta P_T^h + \Delta P_{LEC}\right) \cdot t \cdot c_w = f(I_h, R_T, R_0, s, s_n, l, \sigma, c_w)$	$[\frac{EUR}{time\ unit}]$
$E_{\Delta W_P}^{THD_I}$	$E_{\Delta W_P}^{THD_I} = C_{\Delta W_P}^{THD_I} - C_{\Delta W_P}^{THD_I,minimizat} = f(I_h)$	$[\frac{EUR}{time\ unit}]$
$C_{AHF,max}^{THD_I}$	$C_{AHF,max}^{THD_I} = f(I_h, TRB = 5ani)$	[EUR]
E_{totale}	$E_{totale} = C_{W_P}^{final} < C_{W_P}^{initial} = f(Investiții)$	$[\frac{EUR}{time\ unit}]$

3.4. Developing the Human-Machine Interface (HMI)

The development of the Human Machine Interface (HMI) was based on the creation of an online, user-friendly system to supervise the analysis processes and their results. Also, by using an open-source platform, automatic alarm functions were implemented, based on a set of rules that can be modified at any time, in order to ensure compliance with the legislation in force or adaptation to the targets imposed by the organization (the actual beneficiary of AEMS).

The AEMS therefore ensures that the results of the analysis modules are displayed in an intuitive, user-friendly format for all the organization's decision-makers, from the technical managers - in the case of users with an energy use of more than 1,000 t.e.p./year, these will be authorized Energy Managers (detailed real-time reports) to Senior Management (regular reports, with a focus on the economic and financial implications).

In order to translate the Analysis Modules into an integrated, "user-friendly" system that can be used efficiently by operating staff, technical managers and Top Management of the energy contour, in this last stage of SAME development, the Human Machine Interface (HMI) has been designed and built.

The AEMS was developed using the Py programming language (Python) and the Jupyter Notebook code builder, which allows the use of a language agnostic (Py, C++, Java, etc.). The databases built both for running AEMS and by AEMS itself (the results of the analysis modules) are based on a PANDAS DATAFRAME structure.

After the development of AEMS, the HMI component was developed using two separate modules. First, for the evaluation of the metrics (results of the energy analysis modules), the StatsD Network Daemon (a program running as a background process, not controllable by the user) running on the Node.js platform was used, which checks the transmission of metrics over UDP or TCP protocols and then transmits their aggregated values to one or more back-end services.

To ensure high redundancy, two serialized back-end services were used. The first layer consisted of using the open-source PROMETHEUS platform. This platform collects and stores the metrics as time series data (data is stored with the time label at which it was retrieved and with other optional key-value pairs as labels). PROMETHEUS therefore allows the construction of a multidimensional data model.

After providing the first layer of metric aggregation, in order to ensure a more user-friendly interface, the Open-Source GRAFANA platform was used. It allows the construction of a graphical interface structured on both real-time and aggregated data.

It also allows the design of alarms/notifications/reports, depending on the metrics displayed and has the facility to ensure their transmission both via email and via a dedicated mobile app, thus minimizing the response time of technical managers when abnormal situations occur in the operation of the monitored energy contours.

All the Analysis Modules developed in the work have been introduced in this platform. Taking into account the AEMS performance (in terms of data acquisition speed and computation/processing time), the GRAFANA interactive platform was configured with a 5 second auto-update rate (all displayed values are automatically updated every 5 seconds).

4. Implementing the AEMS. Case Studies and Results

The AEMS has been implemented and tested on a number of six distinct energy boundaries as follows:

- An industrial user in the automotive industry in Sibiu county - AEMS was installed at the point of common coupling of the energy boundary and at a transformer substation supplying power to approximately 25% of the industrial platform - four monitored circuits (PCC, the secondary of the 20/0.4 kV power transformer and the secondaries of two 0.4/0.12 kV transformers supplying a production section),

- At the level of two office buildings in the same real estate project in Bucharest (at the level of the power transformer secondaries supplying the buildings and at the level of the HVAC power supply) - four monitored circuits (2 at each building),
- At the level of a transformer substation belonging to SDEE Transilvania SUD, located in Brasov county (at TDRI level) - four monitored circuits.

4.1. Case Study – Identifying PQIIA – Limiting high current harmonics regime

As part of the research to demonstrate the importance of minimizing THD_I in the end-user distribution network, a case study on the technical and financial viability of implementing THD_I reduction solutions was carried out.

The experimental research carried out for the elaboration of this case study and for the development of the module for the analysis of the implementation potential of the PQIIA concerning the reduction of the electric current distortion regime, was based on an industrial user carrying out its current activity according to a NACE code 2031 - Manufacture of miscellaneous parts and accessories for motor vehicles and motor vehicle engines.

During the period prior to the analysis, it had undergone a series of technical events, concentrated in two production areas where several CNC (Computer Numerically Controlled) machines were operating. The CNC machines are equipped with 3-axis DC electric drive systems (more than 12 DC electric motors/CNC machine).

These CNC machines are powered by transformers with an apparent power rating of 112.5 kVA and voltage rating of 0.4/0.12 kV, with a Yy6 connection group - designed and manufactured in the USA. Over the last four years the user has replaced more than 40 transformers of this type as a result of complete breakdown, incurring total additional costs of more than EUR 30,000/year, plus financial losses of more than EUR 8,500/year as a result of the temporary cessation of production.

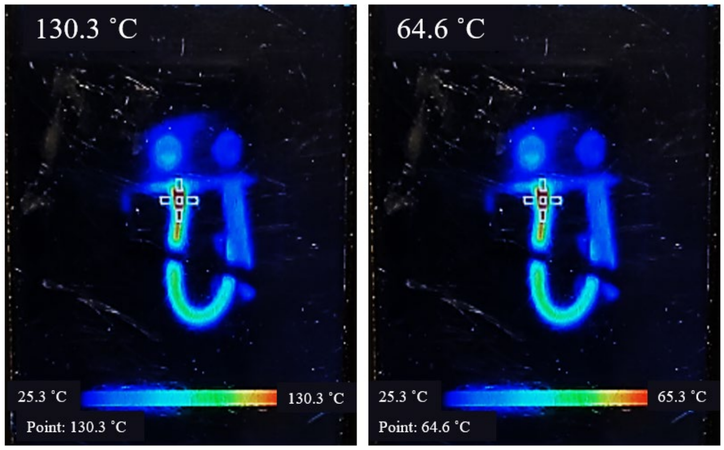
The impact of distorted operation is all the more significant as the analyzed receivers operate continuously (8,600 hours/year), with the exception of possible maintenance/repair periods (on average 160 hours/year).

The analysis carried out as part of the experimental research identified that the type 1 and 2 CNC machines generated significant harmonic electric current disturbances, mainly due to the power conversion systems (rectifiers) used to power the multiple DC motors.

The next step was to carry out a thermographic analysis of the power transformers feeding these CNC machines, which identified that all the 0.4/0.12 kV power transformers and the power lines connecting them to the CNC machines were operating in a severe overload regime (see ***Figure 4.1.1***).

The operating temperature of the power line connected to the secondary terminal of the power transformer was 139.6 ˚C, more than 70% higher than the manufacturer's guaranteed nominal operating temperature (65-70 ˚C).

By reducing the level of harmonics of rank 3 (influence on the Neutral conductor), 5, 7 and 9 as a result of the installation of an Active Harmonic Filter (AHF) system, the user no longer encountered situations resulting in the failure of power transformers and thus eliminated both additional power and energy losses in the distribution network and non-energy related financial losses (equipment replacements and production downtime).



a) b)

Figure 4.1.1 – Thermographic analysis of L3 phase from the power supply of a type 1 CNC machine a) before implementing the THDI minimization project, b) after the implementation of the project

In order to experimentally develop the analysis model, a measurement campaign was carried out at the secondary terminals of the 0.4/0.12 kV power transformer.

Following the measurement campaign at the secondary level of the transformer in the operating state (T1), carried out over a period of 72 hours, with a data acquisition rate of 1 data packet per second, using a Class A three-phase power quality analyzer (FLUKE 1734), the database used for testing the calculation module was built.

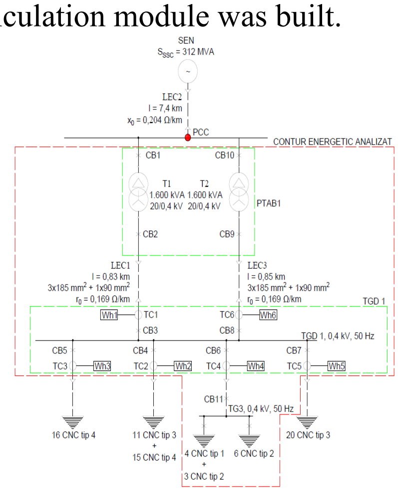


Figure 4.1.2 – The single line diagram of the analyzed energy boundary – PQIIA Module

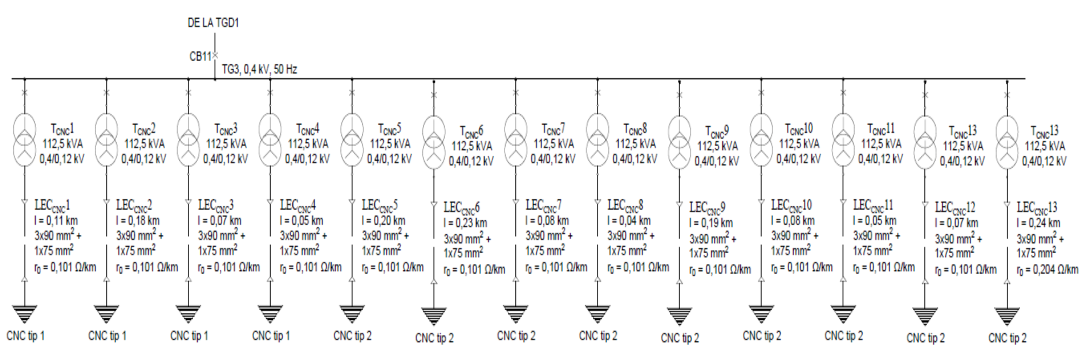


Figure 4.1.3 – The single line diagram of TGD 3 – PQIIA Module

Taking into account the structure of the Transformer Substation, shown in ***Figure 4.1.2***, measurements were performed on each output of the TGD to identify the relevant source of electric current harmonics. It was thus identified that the relevant source of electric current harmonics is represented by TG 3 (General Table 3) - see **Figure 4.1.3** - as a result of the grouping at this point in the network of the CNC machines with the most significant contributions to electric current harmonic distortion. Significant current unbalances were also identified, highlighting a reduced concern for phase load balancing. In this regard, the impact of electric current harmonics on the energy performance associated with LEC1 was determined.

By applying the methodology presented in Chapter 3, the Cost-Benefit Analysis carried out shows that the project can generate, over the study period (10 years), a Net Present Value (NPV) of more than EUR 1.4 million, with a Total Present Cost (TOTEX) of EUR 650,000. The gross payback period is only 3 years, compared to the manufacturer's guaranteed lifetime of the AHF of 10 years. It has therefore been demonstrated that this module can significantly contribute to increasing the energy and financial performance of end-user distribution networks.

4.2. Case Study – Active Power Demand Forecast

The energy boundary on which the Machine Learning algorithm has been developed, tested and extended is a tertiary energy sector end-user - office building. The air conditioning system is responsible for more than 70% of the annual electricity demand, with both heating, cooling and domestic hot water provided by electrical systems.

In the first stage of development of the machine learning and prediction algorithm, only the dependency between the active power input and the average outdoor temperature was considered. The parameterization of the neural network was performed through successive iterations, aiming to identify the optimal values of the hyperparameters leading to the best form of active power demand forecasting. At the end of the learning/testing process, after the 20 epochs (successive runs through the available data), a root mean square error of 15.96 kW (<0.02%) was obtained. The evolution of the measured power demand, outdoor temperature and the forecasted power demand over the learning / testing cycles are presented in ***Figure 4.2.1***.

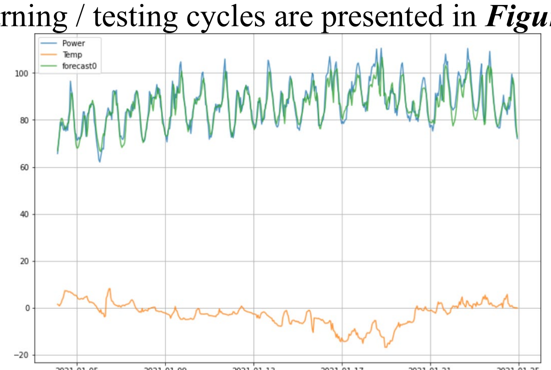


Figure 4.2.1 – The evolution of the measured power, in kW (blue) and forecasted power demand by the LSTM RNN, in kW (green), depending on the outdoor temperature (orange), in ˚C

For further testing of the developed genetic algorithm, a set of data provided by the Department of Energy (DOE) from a tertiary sector Office Building located in Richland Township, Benton County, Washington State, USA was used.

The data provided included building power input and average outdoor temperature, aggregated hourly, over three calendar years (2018-2019-2020). The results obtained by applying the ML algorithm described above are shown in ***Figure 4.2.2*** and ***Figure 4.2.3***.

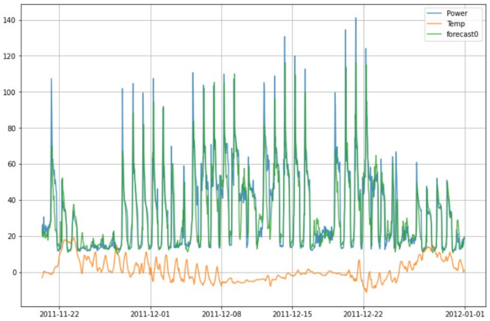


Figure 4.2.2 – The evolution of the measured power, in kW (blue) and forecasted power demand by the LSTM RNN, in kW (green), depending on the outdoor temperature (orange), in ˚C – DOE dataset

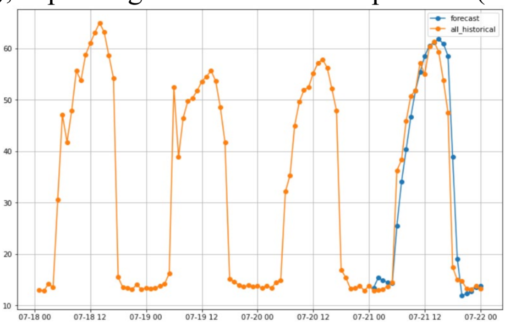


Figure 4.2.3 – The forecasted power demand, in kW (blue) and the actual measured power demand, in kW (orange) – DOE dataset

To extend the machine learning algorithm from one variable external factor to five variable external factors, as presented in Chapter 3, historical consumption data for a period of 4 calendar years was used to regenerate the learning model of the algorithm using the same hyperparameters identified previously. The prediction of variable external factors was performed by calling the API created.

Taking into account the specificity of the analyzed energy boundary - office building, the absorbed electrical power depends directly on the building occupancy. Since at the time of writing the transit of people in the building is not properly monitored/quantified, additional errors due to this variable occur, which however the prediction algorithm detects and corrects, on the fly, as can be seen in ***Figure 4.2.4*** - each point represented in the figure represents the hourly (60 minutes) aggregated electric power. The results are similar for all data aggregation categories.

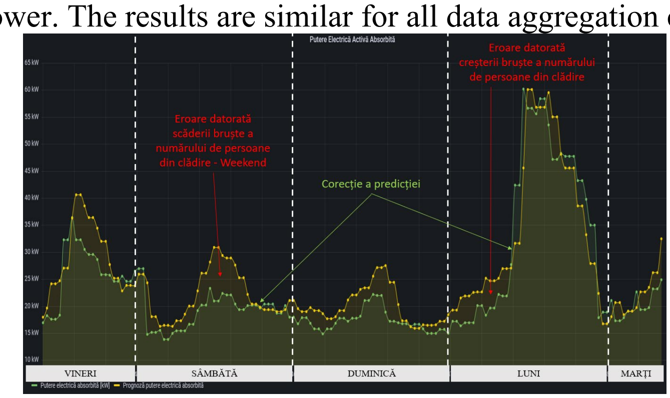


Figure 4.2.4 – Power demand forecast (yellow) vs. actual power demand (green)

The forecast of active power demand is carried out in three distinct steps:

1. A forecast is made for the next hour, useful for participation in the Balancing Market (BM): for example, at 15:00, the quantities of electricity to be used in the next four (4) settlement

intervals - defined by 15-minute intervals - are forecasted. This forecast is essential to maximize the financial efficiency of participation in the balancing market,

2. A forecast is made for the next hour: e.g., at 15:00 the amount of electricity to be used in the next 60 minutes, i.e. until 16:00, is forecasted. This forecast is essential for estimating the energy performance of the energy subsystems related to the analyzed energy boundary. In the presented case study, the Significant Energy Use is represented by the HVAC system (Chillers + Air Handling Units + Circulation Pumps + Fan Coils). Forecasting the electricity use for the next hour allows to evaluate the energy performance of the HVAC system in advance, based on the previous performance,
3. A forecast is made for the next day: for example, at 00:00 each day, the amount of electricity to be used in the next 24 hours is forecasted (with a forecast step of 60 minutes). This forecast is essential both for participation in the Day-Ahead Market (DAM) and for the overall assessment of the energy performance of the analyzed energy boundary, in advance.

The results provided by the Machine Learning algorithm generate the following benefits:

1. The possibility to evaluate, in advance, the energy performance of the analyzed energy boundary in order to identify possible deficiencies in the operation / parameterization of the installations,
2. The possibility to optimize energy trading in the DAM, from the point of view of the Beneficiary, in order to increase its ability to forecast the energy demand;
3. In the case of large electricity users, it leads to maximizing the efficiency of participation in the Balancing Market, in the sense of increasing the efficiency of consumption forecasts.

Also, by using the forecast electricity demand values, it is possible to predict the evolution of energy performance indicators at the level of the monitored energy subsystem or even at the level of the overall energy boundary.

The machine learning algorithm achieves very good performance, with an aggregate 24-hour forecast error of only 1.09%, generated mainly by the variability of the variable external factors (forecast vs. realized) and the lack of quantification of other variable factors relevant for the forecast (such as hourly occupancy of the building/rooms and habits of the building users - temperature regulation in the rooms). The variable factors considered in the presented case study are relevant to the energy analyzed energy boundary, each of them generating a quantifiable impact on the electricity demand. It is necessary, however, that in the actual training phase of the machine learning algorithm, the possibility that some of the variable factors initially considered do not generate a quantifiable impact or generate an impact that can be quantified by a smaller number of factors, thus optimizing the learning time and minimizing the deviations due to forecast errors for them, is also analyzed. Also, in order to increase the accuracy of the forecast it will be necessary to quantify other variable factors as presented in the thesis (e.g. number of people served, specific productivity, etc.).

5. Conclusions. Personal Contributions. Further Research Directions

5.1. Conclusions

Following the development, implementation, testing and improvement phases of the Advanced Energy Management System, the following conclusions on its technical functions emerge:

- ✓ It is necessary to measure, in real time, with a periodicity of 1 data set per second (up to 256 samples per cycle) the data necessary for the application of the proposed calculation methodologies - a lower sampling rate does not allow capturing, with a sufficient degree of accuracy, the values necessary for the determination of the Power Quality Indices while a higher sampling rate becomes financially unfeasible,
- ✓ For the normalization of the Energy Performance Indicators, it is mandatory to monitor, in real time, the relevant variable factors (average ambient temperature, relative humidity, precipitation, daylight level etc.) with a periodicity of 1 data set per hour - a higher sampling rate does not increase the accuracy of the forecast, as the variation over shorter periods of time of the variable factors is not significant,
- ✓ For the successful application of Machine Learning procedures, it is necessary to acquire, in real time, the relevant forecast of the variable factors (average ambient temperature, relative humidity, precipitation, natural light level), with a periodicity of 1 data set per hour - forecast for the next 48 hours - a higher sampling rate does not lead to an increase in forecast accuracy, as the variation over shorter periods of time of the variable factors is not significant while the use of forecasts over periods longer than 48 hours introduces a significant error, which will propagate into the ML algorithm,
- ✓ In order to quantify the interdependence between the Power Quality Indices and the Energy Performance Indicators, it is necessary to ensure a high level and depth of Assessment of the selected Power Quality Indices:
    - Voltage Waveform Factor,
    - Voltage Peak Factor,
    - Voltage dips (number, magnitude, and frequency of occurrence),
    - Voltage spikes (number, magnitude, and frequency of occurrence),
    - Voltage unbalances - Voltage unbalances factor,
    - Electric current unbalances - the electric current unbalance factor, calculation of the potential to reduce losses by correct balancing of network phases,
    - Total harmonic distortion factors of electric current and voltage - harmonic rank analysis and THD_U/THD_I analysis.
- ✓ In order to allow normalization of the energy performance indicators, over time, it is necessary that the assessment of the total active power input is carried out in relation to the relevant variable (or static) factors for the energy contour - in the thesis five relevant variable factors were considered (temperature, wind speed, degree of cloudiness, degree of daylighting, relative humidity),
- ✓ For the prediction of the active power demand in relation to the predicted variable factors, thus normalizing the predicted power demand, it is necessary to apply Machine-Learning procedures. In the absence of these procedures, normalization and forecasting can be performed by simplified mathematical methods (presented in the paper, in Chapter 2),
- ✓ It is necessary to forecast the demand for power and therefore energy according to the relevant variable factors, in order to assess the potential for implementing Energy Performance Improvement Actions, such as flattening of the load curve, development of distributed power generation projects, implementation of active filtering systems for electric current harmonics or reactive power compensation systems,

- ✓ Continuous analysis of load curve indicators is mandatory, both to identify the potential for implementation of load flattening actions and to assess the performance of such projects over time, post-implementation,
- ✓ It is mandatory to analyze power and energy losses in the monitored distribution network, both to identify the potential for implementing actions to flatten the load profile or improve the PQI and to assess the performance of such projects over time, post-implementation,
- ✓ In order to encourage the implementation of Load Curve Flattening projects, the system shall carry out, at relevant intervals (monthly), a techno-economic analysis of the potential for the application of Load Curve Flattening processes through the use of renewable energy sources and electricity storage systems, which shall satisfy, as a minimum, the following functionalities:
    - o Iterative sizing of the optimal size of a PV+BESS hybrid system ensuring technical-energy efficiency,
    - o Life-cycle techno-economic analysis of the system, taking into account the degradation of the photoelectric modules, the loss of storage capacity of the electrochemical batteries and the evolution of the electricity price over the study period.
- ✓ In order to encourage the implementation of PQI Improvement projects, it is necessary to apply Machine-Learning processes for the prediction of average annual losses due to the distorted electric current operation of grid elements, which should perform a techno-economic analysis of the potential application of these actions, using the proposed Opportunity Cost Analysis methodology.

By analyzing the results obtained from the development, implementation, testing and validation of the AEMS, it can be concluded that:

1. The application of correct phase balancing procedures is technically and financially justifiable only if the average electrical current unbalance factor exceeds 20%. Otherwise, the benefits obtained by this action are small in relation to the work and investment required,
2. The implementation of power factor correction measures is technically justifiable if the total average power factor at the energy boundary level is less than 0.8 for at least 50% of the duration of a year and is less than the limit of 0.65 for at least 10% of the duration of a year,
3. Monitoring the voltage curve unbalance factor is of particular interest for users owning/operating three-phase motors, as values above the 2% limit will lead to a drastic reduction in their lifetime,
4. At present, the application of Load Curve Flattening procedures is not viable from a technical-economic point of view if it is not financially supported by a solution for an overall reduction in the amount of electricity absorbed by the user, due to the non-existence of a tariff scheme differentiated by hourly intervals,
5. Encouraging the application of technically simpler LCF procedures - Peak Shaving / Peak Shifting using electricity storage systems can be achieved by developing a tariff scheme that should have an off-load tariff of maximum 50% of the peak load tariff for the load curve analyzed in the PhD thesis,
6. The application of procedures to limit the negative effects generated by the operation of electricity distribution networks in distorted electricity regimes is attractive even

considering only additional power and energy losses. If these regimes lead to additional faults/damage/financial losses in the analyzed energy boundary, as has been demonstrated, PQIIAs become even more attractive and acceptable to the user's top management,

7. The implementation of Machine Learning (ML) algorithms to increase the accuracy of electricity consumption forecasting can generate major financial benefits, especially for large users who are obliged to participate in the Balancing Market. In the case study presented, the user achieved a reduction in expenses associated with participation in the Balancing Market of EUR 6,500 in only 4 months of operation by minimizing forecast error. Prior to the implementation of the ML process, energy consumption estimates were made exclusively on a historical basis (future settlement interval = previous settlement interval of the current day and month of the previous year). The ML algorithm becomes operational and efficient after at least one year of the AEMS operation (hourly aggregated records). Maximum efficiency is reached after aggregation of data for a period of two years (hourly aggregated records).
8. The implementation of machine learning (ML) algorithms for obtaining input data in techno-economic analyses can significantly increase their quality and accuracy, as observed in the analysis of the PQIIA application, even though they only took into account energy-related aspects, and not operational aspects (material damage due to distorted electric current operation). By integrating AEMS with ERP / SAP, such particular elements can also be taken into account - thus integrating the energy management system with the user's financial and operational management systems.
9. The development of SAME using Open-Source solutions and systems (Python / Jupyter Notebook / Prometheus / Grafana etc.) easily allows both technology transfer to Pay-to-Use platforms and community access to AEMS results for continuous development and improvement.
10. The technical-economic viability of implementing an Advanced Energy Management System has been clearly demonstrated in the thesis, with the actions identified and proposed by the AEMS having a gross payback period of less than 4 years (including the actual cost of the AEMS).

5.2. Personal Contributions

During the PhD training period, starting in 2018, the system for monitoring energy flows and variable factors was designed and implemented in several distinct energy boundaries relevant to the objectives of the PhD thesis, with personal contributions consisting of:

1. Designing the AEMS logic scheme,
2. Participation in the experimental development phase of the hardware and software part of two three-phase power quality analyzers based on Open-Source systems and modelling (in partnership with NET ENERGY and SENSIX) - devices that can be produced and sold at a competitive price in the market, which consisted of:
   2.1. Hardware development of analyzers - personal contributions in the choice of microchip used for Fourier analysis and in the choice of electrical current sensors used,
   2.2. Software development of the analyzers - personal contributions in the development of models for the calculation of PQIs at the level of the microchips

used, in order to minimize the size of the data packets transmitted from the analyzer to the AEMS server,

2.3. Power Quality Analyzers testing and validation - personal contributions in the performing electrical measurement campaigns using a set of three-phase Class A power quality analyzers as a benchmark.

3. Design and construction of the database used to monitor, aggregate and store the electrical and non-electrical measurements made,
4. Conducting energy measurement campaigns at six distinct energy boundaries, in which the aforementioned three-phase power quality analyzers were tested and validated and the information needed for testing, validating and improving the AEMS (both energy information and relevant variable factors as presented in the thesis) was acquired,
5. Development of seven technical and economic analysis modules, three of which use recurrent neural networks - machine-learning procedures,
6. Design and construction of the databases necessary for the application of the technical-economic analysis modules,
7. Software development of the AEMS, including machine-learning procedures and modular implementation of techno-economic analysis modules,
8. Implementation of the AEMS at the level of the six energy boundaries in order to test and validate the proposed methodology and the developed analysis modules,
9. Demonstrating the replicability of the proposed AEMS by installation in similar energy boundaries (in terms of electricity use sector),
10. Carrying out more than five case studies demonstrating the functionalities and technical, energy and financial benefits generated by proposed AEMS.

The capabilities of SAME and, implicitly, of the proposed algorithms have been tested and demonstrated, and the results of the various R&D stages have been disseminated through the publication of sixteen (16) scientific articles indexed in ISI and BDI databases, including:

- One (1) article was published in the UPB Scientific Bulletin, Series C,
- Six (6) articles have been defended in ISI indexed international conferences,
- One (1) article was published in a BDI journal,
- Eight (8) articles have been defended in BDI indexed international conferences.

5.3. Future research directions

As a result of the experimental research and development work carried out in the thesis, several future research directions have been identified that may be of interest from the perspective of Energy Efficiency targets and, implicitly, the fight against climate change.

Although the AEMS has been designed with the overall objective of system modularity, further research is needed on the potential application of the system for small (in energy terms) end-users - SMEs (small and medium-sized enterprises), as this sector has a significant share in total energy needs.

A key direction, which can lead to a significant change in the behavior of energy end-users in terms of flattening the load curve associated with them at the level of electricity distribution network elements, is the development of a Dynamic Tariff Mechanism (DTM), by network zones, through which the use of energy at no-load is rewarded and the use of energy at peak load is penalized.

Another key direction that can lead to increased energy performance of DSO-owned electricity distribution networks may be the development of a Demand Response (DR) system, by grid zone and user type. This may be attractive in the residential sector, but it would entail significant costs on the DSO side to replace the electrical switchboards in homes (in such a way as to allow selective remote operation of specific circuits - e.g.: powering the fridge / washing machine / air conditioning). Detailed research into public receptiveness and the results of a cost-benefit analysis may be needed to assess the technical, financial, and commercial viability of this type of action.

Also, the tertiary sector (shopping centers and logistics warehouses) is extremely attractive for the implementation of such a DR system, due to the large capacities of the refrigeration and cooling systems owned by users in this sector.

With regard to the development of RES generation capacities, the results of the LCF Potential Analysis Module justify the legal, commercial and financial analysis of changing the main axes of reimbursable/non-reimbursable financing in such a way that end-users wishing to become active users are encouraged to implement exclusively hybrid systems (generation + storage), thus becoming direct participants in the process of flattening the load curve related to the electricity distribution network elements.

Financing of conventional projects (only photo-electric power plants) from public sources is not justified in the current market conditions (continuously decreasing investment costs and high electricity prices), leading to extremely attractive financial indicators (e.g., IRR values of more than 30-40%/year).

Regarding the applicability of Machine Learning / Artificial Intelligence procedures in the energy services sector, based on the results of the scientific report, it is possible to determine the optimal structures of monitoring systems such as Building Management System (BMS) / Warehouse Management System (WMS) etc. leading to an optimized data flow in terms of the quality of the recorded data: measurement points, frequency of data acquisition, level of aggregation, which is extremely important for the implementation of Digitized Energy Management procedures.

Selective Bibliography

[1] Espe E., Potdar V. și Chang E., ”Prosumer Communities and Relationship in Smart Grids: A Literature Review, Evolution and Future Directions,” Energies, Vol. 11, 2018.

[2] Meng K., Dong Z.Y., Xu Z., Zhen Y. și Hill D.J., ”Coordinated Dispatch of Virtual Energy Storage Systems in Smart Distribution Networks for Loading Management,” IEEE Transactions on Systems, Man, and Cybernetics: Systems, Vol. 49, Issue: 4, pp. 776-786, 2017.

[3] Solanki B.V., Raghurajan A., Bhattacharya K. și Canizares C.A., ”Including Smart Loads for Optimal Demand Response in Integrated Energy Management Systems for Isolated Microgrids,” IEEE Transactions on Smart Grid, Vol. 8, Issue:4, pp. 1739-1748, 2017.

[4] Elmouatamid A., Ouladsine R., Bakhouya M., El Kmoun N., Zine-Dine K. și Khaidar M., ”A Model Predictive Control Approach for Energy Management in Micro-Grid Systems,” 2019 International Conference on Smart Energy Systems and Technologies – SEST, DOI: 10.1109/SES.2019.8848995, 2019.

[5] Chen C., Duan S., Cai T., Liu B. și Hu G., ”Smart energy management system for optimal microgrid economic operation,” IET Renewable Power Generation, Vol. 5, Issue: 3, pp. 258 – 267, 2011.
[6] International Organization for Standardization,”ISO 50001 – Sisteme de Management Energetic,” Group of standards, 2018.
[7] Golovanov N., Mogoreanu N., Toader C. și Porumb R., ”Energy Efficiency. Environment. Modern Economy,” AGIR, București, ISBN 978-973-720-695-5, 2017.
[8] Albert A., Gheorghe S., Golovanov N., Elefterescu L. și Porumb R., “Power Quality. Contributions. Results. Perspectives,” AGIR, ISBN 978-973-720-497-4, București, 2013.
[9] Lange S., Pohl J. și Santarius T., ”Digitalization and energy consumption. Does ICT reduse energy demand?,” Ecological Economics, Vol. 176, ISSN 0921-8009, 2020.
[10] Efficiency Valuation Organization, ”International Performance Measurement and Verification Protocol (IPMVP),” 2016.
[11] IEC 61000-40-30/2007, ”Electromagnetic Compatibility (EMC) - Part 4-30: Testing and Measurement techniques - Power quality measurement methods,” 2007.
[12] Leroy P.J., Rousseeuw M. și Annick M., ”Robust Regression and Outlier Detection,” Wiley, ISBN: 978-0-471-48855-2, 2003.
[13] Ochoa L., Ciric R.M., Padilha-Feltrin A. și Harrison G., ”Evaluation of distribution system losses due to load unbalance,” 15th Power Systems Computation Conference PSCC, 2005.
[14] Ignatius O.K., Saadu A.K. și Emmanuel O.S., ”Analysis of copper losses due to unbalanced load in a transformer (a case study of New Idumagbo 2 x 15-MVA, 33/11-kV injection substation),” International Journal of Recent Research and Applied Studies (IJRRAS), vol. 23, Nr. 1, pp. 46-53, 2015.
[15] Greff K., Srivastava R.K., Koutnik J., Steunebrink B.R. și Schmidhuber J., ”LSTM: A Search Space Odyssey,” Transactions on Neural Networks and Learning Systems, Vol. 28, Issue: 10, pp. 2222-2232, 2017.
[16] Uddin M., Romlie M.F., Abdullah M.F., Halim S.A., Bakar A.H.A. și Kwang T.C., “A review on peak load shaving strategies,” Renewable and Sustainable Energy Reviews, http://dx.doi.org/10.1016/j.rser.2017.10.056, 2017.
[17] Van den Bergh K. și Delarue E., “Cycling of conventional power plants: technical limits and actual costs,” Energy Conversion Management, Vol. 97, pg. 70–7, 2015.
[18] Joshi K.A. și Pindoriya N.M., “Day-ahead dispatch of Battery Energy Storage System for peak load shaving and load leveling in low voltage unbalance distribution networks,” Proceedings of the IEEE power & energy society general meeting, pg. 1-5. 2015.
[19] Luo X., Wang J., Dooner M. și Clarke J., “Overview of current development in electrical energy storage technologies and the application potential in power system operation,” Appl Energy, Vol. 137, pg. 511–536, 2015.
[20] Farahzad K., Shahbahrami A. și Ashouri M., ”Optimal Capacity Determination for Electrical Distribution Transformers Based on IEC 60076-7 and practical load data,” International Journal of Engineering and Manufacturing, Vol. 10, pp. 1-11, DOI:10.5815/ijem.2020.01.01,2020.