Experimental Model of the System for Intelligent Power Plant Management

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Abstract—**In the present paper the authors have introduced the definitions, unique attributes and resources of Intelligent Organisations. The authors have justified the abilities to flexibly adjust the supply of electricity produced in micro-installations of Renewable Energy Sources (RES) to the dynamically changing demand on the side of final customers. Additionally, the nature of "learning" of VPP has been indicated, in particular the system learning through utilisation of learning qualities of Artificial Intelligence (AI) generators. The objective function determining system learning has been adopted with regard to balancing the electricity supply and demand, considering non-linearity of RES micro-installations generation and non-linearity of the demand for this type of energy. Having defined the objective function the authors have included the logical and functional presentation of the experimental model of the System for Intelligent Power Plant Management (SIPPM) developed based on available laboratory generators of Artificial Intelligence.**

Keywords—Intelligent Organisation, Virtual Power Plant, management, system learning, Artificial Intelligence

I. INTRODUCTION

Intelligent economic organisations that function in the turbulent environment according to the definition should be flexible, open to change. Transformations occurring in particular entities that create such an organisation, as well as in the whole of it, are a basis of intelligent management.

Based on the conducted literature studies, two subsets of concepts are adopted with reference to Intelligent Organisations: the concept of intellectual potential and the system approach.

In the first case intellectual potential is intellectual contribution – a set of information, knowledge, intellectual property, skills: individual, team, organisational ones, which can be transformed into tangible capital, but which can presently be digitised as well.

In the second case – the system one, a cybernetic conceptual mechanism is introduced. Similarly to cybernetics, this is a system that constitutes a set of mutually related organisational and technical objects. Frequently, AI tools are utilised as an Integrator – an Intelligent System whose foundations create codified knowledge of experts, aggregated in knowledge databases. Based on learning rules, explaining and reasoning procedures these systems are characterised by the ability of learning, which is an identifier of Intelligent Organisations.

In the present paper the authors have assumed Virtual Power Plants (VPP) as an etalon of Intelligent Organisation. Their structure, distribution, flexibility to dynamically balance the supply of generated electricity and also dynamically changing demand, are associated with the Demand Side Management (DSM) (Pudjianto D., et al., 2008).

II. VIRTUAL POWER PLANT AS ETALON OF INTELLIGENT ORGANISATION

The Virtual Power Plant (VPP) is of a module structure, which imitates the one of a real object. This structure is based on the concept of fast prototyping, which allows for configuring any spatial combinations of real and modelled elements (Vale Z., et al., 2011). In the subject literature it is assumed that VPP is a combination of Renewable Energy Sources (RES), Energy Storage System (ESS), small conventional power plants and interrupted loads, which are capable of ensuring market operations as a single power plant (Thavlov A., Bindner H.W., 2015). Also, VPP is defined as a space where innovative solutions of dispersed generation are integrated, this concerns in particular RES micro-installations (in Europe this is assumed to be 40kW (Kuceba R., et al., 2014). In the spatial reference – VPP is also a concentration of dispersed generation in one, logically linked system, where energy sources are installed close to final consumers. It needs to be mentioned that resources of all entities – dispersed generation, including RES micro-installations, are co-shared in the structure of VPP. While referring to the abovementioned definition it also needs to be stressed that the physical and logical integrator of the dispersed entities/resources of VPP are Smart Grid networks. They co-share dispersed resources on the side of electricity producers (Hernandez L., et al., 2013) and simultaneously resources on the side of final customers (the demand side). The ability of making own resources available ensures access to its all resources, which is undoubtedly a chance to improve organisational flexibility against changes occurring in the environment of VPP's functioning – on-demand-resources (Kuceba, M. et al., 2018), (Markovic D.S., et al., 2013), (Hatziargyriou N., et al., 2007).

It is assumed that the dispersed production potential of VPP, non-linearity of electricity generation/production, especially in RES micro-installations, should be stimulated and enhanced through the "learning" capabilities. The "learning" abilities of particular units in the VPP's structure

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impact to a larger extent the development of an enterprise than its autonomous production capacities (technological ones) (Markovic D.S., et al., 2013).

VPP, where the intellectual potential plays a dominant role, through „learning" becomes highly flexible in identifying changes, reacting, and adjusting to the turbulent environment. It needs to be stressed here that in case of VPP it concerns continuous changes of the demand for electricity and preferences of final customers (e.g. the dynamically changing demand for energy conditioned by the season of the year, time of day, atmospheric conditions). The intellectual potential and "learning" capabilities of such an organisation are also a basis for defining Virtual Power Plants as Intelligent Power Plants, that is "learning" ones. In accordance with the introduced discussion regarding Intelligent Organisations also in case of Intelligent Power Plants it is possible to adopt the concepts of intellectual potential and system approach, including system learning (Dietrich K., et al., 2015.

III. Artificial Intelligence Generators In Managing Virtual Environment

An important role in satisfying the energy demand in the world play photovoltaic systems/farms (PV) and wind energy conversion systems (WECS), as well as the distinguished in the present paper RES micro-installations. Attempts have been made to improve the effectiveness of this type systems of renewable energy through application of various approaches aimed at reducing their non-linear availability (instability in energy generation). Several approaches are being developed to manage the emerging dispersed potential – this concerns in particular RES micro-installations through, among others, aggregation of these sources (of limitless characteristics of their available capacity) in the structures of VPP and Smart Grid (Vale Z., et al., 2011). It seems that apart from these organisational and informatic projects (system ones), a vital importance needs to be assigned to intelligent projects, in particular Artificial Intelligence (AI) (Liserre M., et al., 2010). According to the literature on the subject intelligent projects implemented in the structures of VPP and Smart Grid stimulate the capacity growth of renewable energy system and dispersed RES micro-installations (Karabacak K., Cetin N. 2014). Artificial Intelligence Generators such as, among other, Expert Systems (ES), Artificial Neural Networks (ANN), Genetic Algorithms (GA) or Fuzzy Systems (FS), can be applied in a number of areas in modelling, simulating and controlling renewable energy systems. Presently, this also concerns RES installations in the structures of VPP. Therefore, in order to present it in a synthetical manner, based on literature review, in Table 1 the authors have summarised selected research areas of Artificial Intelligence application in the management and control processes of RES micro-installations (Fadaeenejad M., et al., 2014), which can operate in the dispersed structure of VPP.

TABLE I. SELECTED RESEARCH AREAS OF AI APPLICATION IN THE MANAGEMENT AND CONTROL PROCESSES OF RES MICRO-INSTALLATIONS IN THE STRUCTURE OF VPP

Generator/intelligent system	Research areas/Application
Artificial Neural Networks (ANN) (Karabacak K., Cetin N. 2014)	Modelling, simulating and controlling a hybrid system that includes photovoltaic sources (PV) and wind energy conversion system (WECS)
Artificial Neural Networks (ANN) (Azadeh A,, et al., 2013)	Application of neural network of Multi Layer Perceptron (MLP) topology for optimum assessment and forecast of renewable energy consumption with the consideration of environmental and economic factors
Extreme Learning Machine (ELM) (Shamshirband S., et al., 2016)	Estimating the distribution/coefficients of wind speed in Weibull probability distribution so as to determine the turbine capacity.
Fuzzy System (FS) (Datta M., Senjyu T., 2013)	System for controlling dispersed photovoltaic inverters and energy storage systems (ESS), to power electric vehicles (EV) of Megawatt (MW) class. The method is simulated through the consideration of bi-directional energy and information flow between the supply and demand sides in a large electro-energy system.
Fuzzy System (FS) (Pahasa J., Ngamroo I., 2018)	System for integrating in a micro-grid (MG) plug-in hybrid electric vehicles (PHEV), photovoltaic generators (PV) and energy storage systems (ESS), to control the frequency.
Fuzzy System (FS) (Suganthi L., et al., 2015)	Fuzzy logic controllers (FLC) applied to control the intermittent energy flow from Renewable Energy Sources.
Expert System (ES) (Kasaei M.J., et al., 2017)	Energy Management System (EMS) called Virtual Power Plant (VPP) with embedded RES micro-installations and energy storage systems (ESS). Application of the developed competitive algorithm to minimise total operating costs, considering the cost of energy losses at 24-hour intervals.
Micro-Grid (MG) with embedded orientation mechanisms (Koohi-Kamali S,, et al., 2014)	Reduced oscillation of power generated in photovoltaic systems and as a result of changeable loads, through control of the co-operating battery power plant.

Source: own elaboration based on literature review

A continuation and supplementation of these studies constitute also experimental works of the authors, which concentrate on balancing the electricity supply and demand in the VPP's structure.

IV. System For Intelligent Power Plant Management

In this part of the paper the authors have presented the module structure of the developed model of the System for Intelligent Power Plant Management (SIPPM) – a virtual "brain" of the described dispersed Intelligent Power Plant adapted in the structure of VPP. It needs to be stressed that the developed model is of experimental and conceptual nature. It has been developed based on the available to the authors at the Faculty of Management of Czestochowa University of Technology laboratory generators of Artificial Intelligence (CAKE, PC-SHELL, STATISTICA NEURAL NETWORKS, MATLAB FUZZY TOOLS).

Basically, two integral layers have been distinguished within the structure of SIPPM – operational and analytic ones.

In the operational part, in the context of implementing the adopted objective function and its compounds in the experimental process the following *Knowledge Modules* have been distinguished and developed (Kuceba R., 2011): *Internal Knowledge Module (IKM); External Knowledge Module (EKM).* In the analytic part in turn the following have been adopted and developed: *Explaining and Reasoning Module (ERM); Management (Control) Module of Intelligent Power Plant (MMIPP)* – Fig. 1.

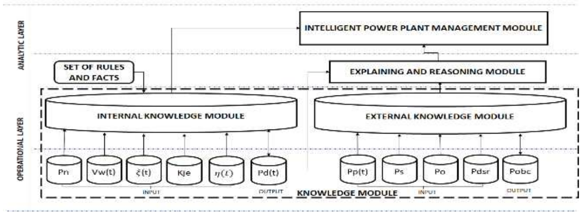

Fig. 1. Modular structure of the experimental System for Intelligent Power Plant Management

Source: own elaboration

V. Knowledge Module

The modules in the operational layer of the proposed model of the System for Intelligent Power Plant Management (SIPPM), i.e. the Internal Knowledge Module (IKM) and the External Knowledge Module (EKM), basically carry out such functions as: scaling, filtering, gathering and aggreging knowledge – acquired from the inside and environment of the Intelligent Power Plant. In the IKM, knowledge is gathered for subsequent transactional hours in the scope of: available and achieved capacity of particular RES micro-installations and its predicted fluctuations, and also knowledge in the scope of weather forecasts, atmospheric conditions (e.g. wind speed in case of a wind farm or level of light in case of photovoltaic cells), planned maintenances, repairs and predicted risk (emergencies – Early Warning System – EWS). The presented variables are aggregated as time series at hourly or daily intervals.

The knowledge generated in the IKM is indispensable to determine electricity supplies, its quality at subsequent transactional hours, in two variants: in total for the whole power plant and for individual RES micro-installations in the structure of the Intelligent Power Plant. Then, in the EKM module, for the determined transactional hours, information is introduced in the scope of actual demand for electricity on the side of final customers, their preferences and capacity of their electricity receivers – which can be managed by the SIPPM (modes: on/off) in subsequent hours of transactional/trading day. In this case variables are also aggregated in time series at hourly and/or daily intervals.

Primary tasks assigned to the IKM in the simulated experimental environment were carried out within CAKE (Computer Aided Knowledge Engineering) and PC-SHELL tools.

Exemplary input attributes: power rating of individual RES micro-installations - Pn, wind speed Vw(t) or level of light (t) in subsequent hours of trading days (historical time series), unit costs of electricity Kje(t), RES micro-installations efficiency with the consideration of their dynamic changes depending on, among others, atmospheric/weather values.

Output value: available capacity Pd(t) of RES micro-installations at a given trading hour.

Based on the input attributes (decision-making factors) and output values (decisions) they have been assigned the authors have developed decision-making conditions for heterogeneous states of the selected RES micro-installations in the form of learning rules/decision-making conditions.

Example:

Ww – ***If*** *((PN ='A_{W1}' AND/OR VW(T) ='A_{W2}' AND/OR/* ξ *(T)= ='A_{W31}' AND/OR KJE='A_{W3}' AND/OR* $\eta(t)$ *='A_{W4}')* ***THAN*** *PD(T)='Y_{W1}'*

VI. Explaining and Reasoning Module

Available capacity *Pd(t)* and values accumulated in the EKM feed the Explaining and Reasoning Module (ERM). At the level of the ERM of the proposed SIPPM forecasts are carried out regarding the demand for electricity generated in particular RES micro-installations. Due to the probabilistic nature of input attributes and output values as well as low correlation coefficients – the authors applied neural networks as a prognostic tool. It was assumed that the forecasts of the demand for electricity (in subsequent hours of the proposed trading day) generated in particular dispersed RES micro-installations were load (demand) schedules of the Intelligent Power Plant. It needs to be mentioned that the forecast accuracy was conditioned by the implemented proces of "learning", selection of weight coefficients and optimum topologies of neural networks. The forecasts were verified with the use of classic *ex-post* measures of forecast accuracy such as: *MAE* – average mean error, *MAPE* – mean absolute percentage error, MSE – mean square error, $\sqrt{MSE}$- square root of means square error (Kuceba R., 2011), (Azadeh A,, et al., 2013).

The authors defined the set of neural networks preserving their structural diversity. Within the confines of the research the following were defined and investigated in the prediction proces of the examined phenomenon, among others: architectures of RBF (Radial Basis Function Networks), GRNN (Generalised Regression Neural Network), MLP (Multilayer Perceptrons) and Linear Networks. Based on the objective function's components priority criteria that determine the proces of learning and „self-learning" of neural networks were defined.

The input attributes in the ERM include: available capacity *Pd(t)*, actual demand for electricity in particular hours of the day preceding the trading day *Pp (t),* average daily load *Pdsr,* consumer's preferences in the scope of utilising: daily peak power *Ps,* and daily minimum power *Po.* The output value: prediction of loads for the Intelligent Power Plant for subsequent hours of the trading day *Pobc*.

Example:

Type	Input1	Input2	Input3	Input4	Input5	Output
Value	Pd(t)	Pp(t)	Ps	Po	Pdsr	Pobc

VII. Intelligent Power Plant Management Module

The Intelligent Power Plant Management Module (IPPMM) in turn fulfils the function of the Decentralised Energy Management System – DEMS)) (Kuceba R., 2011). In this part of the SIPPM the volume of electricity supply in particular RES micro-installations of the Intelligent Power Plant is monitored, resulting from the generated schedules of loads (demand). The Intelligent Power Plant Management Module (IPPMM) generates on the output bi-state or quad-state nominal variables that inform about switching on/off (on the supply side) particular micro-installations and/or switching on/off (on the demand side) electricity receivers by final customers. In the adopted by the authors experimental approach – fuzzy systems have been implemented in the IPPMM so as to support the process of classifying all the knowledge components and adjusting to them bi-state or quad-state nominal variables.

The generated nominal states were implicated while determining the work schedules of the Intelligent Power Plant. In this case the authors utilised available to them fuzzy systems generated in the MATLAB – FUZZY TOOLS environment (Fig. 2). In this application environment linguistic values were assigned to the fuzzy system of their correspondence. Exemplary input attributes include: available capacity *Pd(t)* (generated in the IKM) and forecast load power of RES micro-installations – *Pobc(t),* electricity prices on the electricity market – at hourly and daily intervals - *Cree(t)* as well as unit cost of generated electricity *Kje(t).* The output values are bi-state or quad-state nominal variables (S), switching on/off RES micro-installations and switching on/off electricity receivers on the side of final customers.

The input variables allocated in the aggregated set were subjected to the fuzzification process, within which acute values were fuzzified, which represented relative and absolute measures of the qualities describing the analysed phenomenon. This fuzzification was carried out based on the correspondence functions describing individual input variables.

Three of the abovementioned input variables (*Pd, Kj, Cree*), were described with three trapeze functions. Three linguistic values were generated for these input variables, such as: *low, medium* and *high.* The fourth of the generated input variables – source load power *Pobc* – was described with the use of four fuzzy sets of trapeze correspondence functions and one triangular function. The following linguistic values were distinguished here: idle mode *(bj),* underload mode *(bn),* rating mode *(bzn),* overload mode (bp) and shorting mode *(bzw).*

As it has already been indicated the output variable was the nominal state *S* of the RES micro-installation operation in the structure of the Intelligent Power Plant. Four values of the output variable were determined – four nominal states: *Z* - switching on the RES micro-installation, *W* – switching off the RES micro-installation, *On* – switching on electricity receivers on the side of final customers and *Off* – switching off electricity receivers on the side of final customers. In Fig. 2 the authors have presented the aggregated correspondence functions for particular input attributes and assigned to them output function (decision-making one).

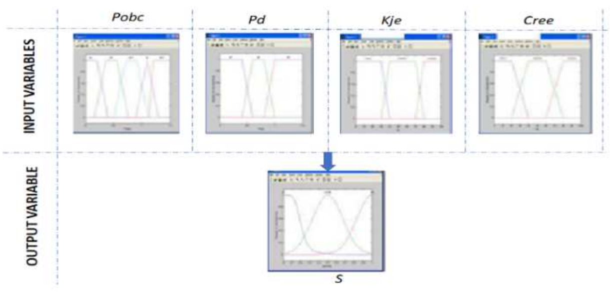

Fig. 2. Variables allocated in the fuzzification process – in the Intelligent Power Plant Management Module (IPPMM)

Source: own elaboration

Based on input attributes (decision-making factors) and assigned to them output values (decisions) the authors have developed decision-making conditions for heterogeneous states of the selected RES micro-installations in the form of fuzzy decision-making rules (according to Fig. 2).

Exemplary fuzzy decision-making rules („learning rules”) allocated in the inference block of the proposed IPPMM have been presented below.

Example:

1. *If (Pobc is bzn) and (P is high) and (Kj is low) and (CREE is high) then (S is Z)*
2. *If (Pobc is bp) and (Pd is high) and (Kj is medium) and (CREE is medium) then (S is On)*
3. *If (Pobc is bn) and (Pd is medium) and (Kj is high) and (CREE is low) then (S is W)*
4. *If (Pobc is bzw) and (Pd is high) and (Kj is high) and (CREE is low) then (S is W)* (2)
5. *If (Pobc is bzw) and (Pd is low) and (Kj is high) and (CREE is high) then (S is W)*
6. *If (Pobc is bzn) and (Pd is high) and (kj is medium) and (CREE is medium) then (S is Z)*

It needs to be mentioned that the developed conceptual and experimental model for Intelligent Power Plant Management, in particular the decision-making module IPPMM was subject to qualitative validation and testing in the simulated real conditions – in the laboratory class “Smart Metering”.

The qualitative verification, as it has already been signalled, regarded forecasts pertaining to power of loads on the demand side – generated in the ERM (neural networks). The quantitative verification was simultaneously an indicator of the selection of neural networks topologies.

VIII. Summary

The experimental model of the System for Intelligent Power Plant Management is another conceptual solution that stimulates the growth of VPP’s value through the expansion of the capacity of intelligent management not only of non-linear RES micro-installations (regarding production) in the dispersed structure, but also dispersed non-linear loads on the side of final customer. Thus, co-sharing the resources of this Intelligent Power Plant in the VPP’s structure is not limited to the supply side. Final customers in such structures of VPP can make available loads of electricity, which can be controlled, among others, by the proposed SIPPM so as to balance the supply and demand in the virtual environment.

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