IMPLEMENTATION OF A SMART GRID SYSTEM IN INDUSTRIAL AND RESIDENTIAL COMPLEXES BASED ON FUZZY NEURAL NETWORKS

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Abstract

The implementation of ‘Smart Objects’ is an important part of the development of adaptive Smart Grid structures. For this class of objects, poorly for malizable factors, such as microclimate parameters, environmental indicators, and consumer load, acquire a significant influence. To solve this, PID controllers are usually used in Smart Objects; however, their accuracy is limited. Fuzzy neural controllers are an alternative solution for the integrated optimization of Smart Objects. This article proposes a scalable model of Smart Object equilibrium by the example of basic utility systems (heating, air conditioning/ventilation and illumination). It was found that the use of fuzzy neural controllers in such systems makes it possible to improve their efficiency by increasing the accuracy of energy consumption forecasts. Control systems based on PID controllers and fuzzy neural controllers in Smart Object were compared only to find that the latter have a higher accuracy.

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Keywords: Smart Objects, distributed objects, PID controllers, fuzzy neural network, fuzzy neural controller, mathematical modeling.

I. Introduction

Turning a regular residential house and an industrial complex into Smart Home and Smart Complex, which used to be a know-how, has long become a standard design solution. However, until now there is no harmonized standard for this class of objects. Typically, to fall into such category of Smart Objects, the building has to have at least one of the following properties:

- the availability of automated control of microclimate devices and information environment;
- the possibility of centralized control of all (or most) subsystems based on a control center (server);
- remote access to the parameterization of adjustable settings;
- a high degree of ‘inward’ (interface with new devices of the lower consumer level) and ‘outward’ (possibility of incorporation into local and global clusters at the level of houses, workshop, premises, etc.) integration;
- local optimization of individual parameters (groups of parameters) according to the consumer algorithm.

The non-specificity of the described class of objects is linked to, first of all, marketing strategies that aim at obtaining the added value from the implemented projects by the ‘reasonable’ introduction of intellectualization into regular solutions. At that, variable indicators are often optimized within the separate circuits, such as heating, lighting, ventilation systems, with a weak (or absent) mutual accounting of adjacent assemblies.

For this reason, in order to standardize approaches to the creation of Smart Objects, it appears reasonable to apply more stringent requirements that are used in the Smart Grid concept for distributed flow objects (power, heat, gas, water supply networks). From this perspective, it would be logical to consider an individual house (apartment) or an industrial workshop as low-level elements of a global development strategy. At the same time, an indispensable prerequisite here would be the availability of all the above properties, combined with the global optimization of energy flows (minimization of losses) and compliance with quality requirements (microclimate parameters, information environment). The main task of controlling such systems is to maintain the required accuracy characteristics (temperature, humidity, illumination of residential/industrial premises) under the presence of poorly malizable disturbances (ambient temperature, natural illumination, user requirements, etc.).

II. Materials and Methods

Let us describe a model of the generalized structure of the considered class of objects by the example of heating, air conditioning/ventilation and lighting circuits (Figure 1). The assumption based on the following aspects:

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Let us present the generalized technological cycle of the Smart Object as the following system of equations:

\[
\begin{align*}
x_1(t) &= \alpha_1 \cdot S_{D1}(T_{d_w}, T_{r_w}) + \beta_1 \cdot S_{D2}(g_a, W_h, W_c) + \gamma_1 \cdot S_{ECG}(\Phi_{li}) + \cdots + n_{x1} \cdot S_{nax1}(Q_n); \\
f_{ex}(t) &= \alpha_0 \cdot T_{ex}(t) + \beta_0 \cdot g_{ex}(t) + \gamma_0 \cdot \Phi_{ex}(t) + \cdots + n_{fex} \cdot S_{nfe}(t); \\
x_2(t + k) &= F[x_1(t), f_{ex}(t), v_{li}(t), T_{env}(t), q_{li}(t)];
\end{align*}
\]

Fig. 1: Smart Object structural diagram

where \(x_1(t)\) is the function of energy consumption for the object operation; \(S_{D1}, S_{D2}, S_{ECG}, \ldots, S_{nax1}\) is the total capacity (kVA) of the respective converter groups; \(T_{d_w}, T_{r_w}\) are the temperatures of the direct and return heat carrier flow (°C) in the heating circuit; \(g_a, W_h, W_c\) are the air flow rate, heating capacity and cooling capacity, respectively, of the air conditioning and ventilation unit; \(\Phi_{li}\) is the artificial illumination (lx); \(Q_n\) stands for the characteristics of other circuits; \(\alpha_1, \beta_1, \gamma_1, \ldots, n_{x1}\) are the coefficients of technological processes; \(f_{ex}(t)\) is the function of interchange with the external environment; \(T_{ex}(t)\) is the temperature of the external environment (°C); \(g_{ex}(t)\) is the volume of air mass available for use at the boundary of the object; \(\Phi_{ex}(t)\) is the natural illumination; \(S_{nfe}(t)\) is the capacity of the energy flow from other external factors located on the boundary; \(\alpha_0, \beta_0, \gamma_0, \ldots, n_{fex}\) are the coefficients of external variables; \(x_2(t + k)\) is the function in period of time \((t + k)\) describing the internal state of the object; and \(v_{li}(t), T_{env}(t), q_{li}(t)\) are the air humidity, air temperature and illumination, respectively, in the generalized model of the objects (in the living/working area).

System (1) presents the energy balance at the creation of the Smart Object, and the third equation contains the consumer algorithm for the required indicators of the
object. The objective functional of optimization can be expressed in the following form:

$$J_{\text{opt}} = \begin{cases} F[x_1(t), f_x(t), u_0(t), T_{\text{env}}(t), q_l(t)] \rightarrow \text{optim}_{\text{consm}}; \\ R \left[ \sum_{i=1}^{m} W_{S_i}(t) \right] \rightarrow \text{min}; \end{cases}$$  \tag{2}

where \(F[x_1(t), f_x(t), u_0(t), T_{\text{env}}(t), q_l(t)]\) is the consumer functional and \(R \left[ \sum_{i=1}^{m} W_{S_i}(t) \right]\) is the functional of energy consumption optimization when the first condition of Expression (2) is fulfilled and \(\sum_{i=1}^{m} W_{S_i}(t)\) in is defined as:

$$\sum_{i=1}^{m} W_{S_i}(t) = S_1(t) + S_2(t) + \cdots + S_m(t)$$  \tag{3}

where \(S_1(t) + S_2(t) + \cdots + S_m(t)\) is the total energy consumption for the implementation of all the sub-structures of the object under boundary conditions as follows:

$$\begin{cases} \sum_{i=1}^{m} S_{i0}(t) = 0; \\ \sum_{i=1}^{m} S_{i1}(t) = 0; \\ \sum_{i=1}^{m} S_{i2}(t) = 0; \\ \cdots \end{cases}$$  \tag{4}

where \(\sum_{i=1}^{m} S_{i1}(t)\) is the sum of internal energy flows and \(\sum_{i=1}^{m} S_{i0}(t)\) is the sum of external energy flows.

### III. Results

PID controllers are frequently used for control channels in modern technological processes, which is due to their relatively simple technical implementation, on the one hand, and acceptable practical performance results (accuracy parameters), on the other. The algorithm of PID controller operation in the framework of the Smart Object can be described as:

$$D(s^{-1})y(t) = C(s^{-1})u(t - k) + B(s^{-1})\xi(t)$$  \tag{5}

where \(y(t)\) is the time distribution of the controller output in the contours of technological processes; \(u(t)\) is the control action; \(k\) is the delay sample; \(\xi(t)\) is the uncorrelated random sequence with zero expectation; and \(D(s^{-1}), C(s^{-1}), B(s^{-1})\) are the polynomials expressed in \(z\)-transformations:

$$D(s^{-1}) = 1 + d_1 s^{-1} + d_2 s^{-2} + \cdots + d_{nd} s^{-n}$$  \tag{6}

$$C(s^{-1}) = 1 + c_1 s^{-1} + c_2 s^{-2} + \cdots + c_{nc} s^{-nc}$$  \tag{7}

$$B(s^{-1}) = 1 + b_1 s^{-1} + b_2 s^{-2} + \cdots + b_{nb} s^{-nb}$$  \tag{8}

In this case, the quality criterion correlated with Expression (2) has the following form:

$$J_1 = E \left[ P(s^{-1}) y(t + k) - R(s^{-1}) r(t) \right]^2 + (Q(s^{-1}) u(t))^2$$  \tag{9}

where \(E[F]\) is the mathematical expectation; \(r(t)\) is the value of control action; and \(P(s^{-1}), R(s^{-1}), Q(s^{-1})\) are the adjustable polynomials of PID controllers of the specific subsystems in the Smart Object.

A system equipped with a PID controller can be regarded as a generalized input of control action, given the predicted output of the control object at the initial set point.

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of the control action. At the same time, the output at moment of time \((t + k)\) can be effectively predicted at moment of time \(t\) if the control action is organized in such a way that all disturbances are neutralized.

The optimal prediction for \(k\) samples ahead is given by the following expression:

\[
\beta^*(t + k) = \frac{F(s^{-1})}{R_d(s^{-1})}y(t) + E(s^{-1}) \cdot C(s^{-1})u(t)
\]  

(10)

where \(\beta^*\) is the predicted value that meets quality criterion (2) and \(F(s^{-1}), E(s^{-1})\) are the polynomials of external actions and PID regulator operation errors, respectively, defined as:

\[
F(s^{-1}) = 1 + f_1s^{-1} + \cdots + f_{(k-1)}s^{-n}
\]  

(11)

\[
E(s^{-1}) = 1 + e_1s^{-1} + \cdots + e_{(k-1)}s^{-(k-1)}
\]  

(12)

Thus, the performance of Smart Object (a residential building or an industrial complex), based on PID controllers, directly depends on the quality of prediction used to adjust parameters \(P(s^{-1}), R(s^{-1}), Q(s^{-1})\) while observing the requirements of the first functional in Expression 2.

Fuzzyneural controllers (FNC) are systems built on artificial neural networks, acting as as an approximating core, and fuzzy input/output for evaluating substantially non-linear processes.

From the point of view of practical implementation, Mamdani and Takagi-Sugeno fuzzy models have the greatest value in the analysis of nonlinear structures that include Smart Objects. When implementing the Mamdani model, we have:

\[
R^u : \text{If } x(t - 1) \text{ is } X_1^u \text{ and, } \ldots, \text{ and } x(t - r) \text{ is } X_r^u \text{ then } y(t) = a^u, u = 1, \bar{u}
\]  

(13)

where \(R^u\) is a set of expert rules for the operation of a fuzzy neural network; \(x(t) = (x_1(t), \ldots, x_m(t))\) is the vector of input variables; \(y(t)\) is the vector of output value; \(X_1^u, X_r^u, Y^u\) are the ranges of values of the corresponding input and output actions of the fuzzy neural network; and \(a^u\) is the constant that presents the amount of the output value to the weighted action of the input values.

Such an implementation is organized according to the MISO principle (multiple input, single output).

In the case of the Takagi-Sugeno model, we have:

\[
R^u : \text{If } x(t - 1) \text{ is } X_1^u \text{ and, } \ldots, \text{ and } x(t - r) \text{ is } X_r^u \text{ then } y(t) = a_0^u + \sum_{i=1}^r y(t - 1), u = 1, \bar{u}
\]  

(14)

Consider the structure of Takagi-Sugeno fuzzy dynamic model (this type was selected as the base for the implementation of FNC due to higher accuracy indicators compared to the Mamdani model), consisting of \(n\) condition action rules with random orders \(r^\theta, s^\theta\) of linear difference equations containing \(k\) input variables \(u_j(t), j = 1, k\) and one output variable \(y(t)\) [22]:

\[
R^\theta : \text{if } y(t - 1) \text{ is } Y_1^\theta, y(t - 2) \text{ is } Y_2^\theta, y(t - r^\theta) \text{ is } Y_r^\theta, u_1(t) \text{ is } U_1^\theta, u(t - 1)
\]
is \( U_{r,k}^\theta \), then \( y^\theta (t) = a_0^\theta + \sum_{i=1}^{\theta} a_i^\theta y(t-1) + \sum_{j=1}^{k} \sum_{l=0}^{s_j^\theta} b_{lj}^\theta u_j(t-l) \) (16)

with fuzzy sets \( U_{j,1}^\theta, ..., U_{j,s_j^\theta}^\theta, j = \overline{1,\bar{k}} \) and \( Y_1^\theta, ..., Y_{\bar{n}}^\theta \), and corresponding membership functions \( U_{j,1}^\theta(u_j), ..., U_{j,s_j^\theta}(u_j) \) and \( Y_1^\theta(y), ..., Y_{\bar{n}}^\theta(y) \), \( j = \overline{1,\bar{k}}, \theta = \overline{1,\bar{n}} \) that characterize the current and past input values \( u_j(t), u_j(t-1), ..., u_j(t-s_j^\theta), j = 1,\bar{k} \) and output values \( y(t-1), y(t-2), ..., y(t-r^\theta) \), and also linear difference equation:

\[
y^\theta (t) = a_0^\theta + \sum_{i=1}^{\theta} a_i^\theta y(t-1) + \sum_{j=1}^{k} \sum_{l=0}^{s_j^\theta} b_{lj}^\theta u_j(t-l) 
\]

(16)

to calculate the output of the \( \theta \)-th rule \( y^\theta (t) \).

The accuracy of output calculation \( \hat{y}(t), t \in [0,T] \) by such a model depends on the correct choice of the type and size of membership functions \( U_{j,1}^\theta(u_j), ..., U_{j,s_j^\theta}(u_j) \)

and coefficients \( Y_1^\theta(y), ..., Y_{\bar{n}}^\theta(y) \), \( j = \overline{1,\bar{k}}, \theta = \overline{1,\bar{n}} \), order \( r^\theta, s^\theta \) of Difference Equation 16 and number of rules \( n \).

The influence of variables \( y(t-1) \) and \( u(t-l) \) on output \( y^\theta (t) \) in the \( \theta \)-th rule is determined by coefficients \( a_i^\theta \) and \( b_{lj}^\theta \); therefore, order \( r^\theta, s^\theta \) can be considered independent of the rule number \( \theta \) and equal to \( r^\theta = \overline{r,\bar{s}} \) and \( s^\theta = \overline{s_j} \).

IV. Discussion

Let us consider the functioning of generalized model of Smart Object (Expression 1) as an example. The presence of time delays and substantially uncertain factors (caused by both consumer requirements and changes in disturbances) in the energy flows transfer is essential for this Object.

For this reason (with the given microclimate indicator control ranges), the quality of consumer optimization produced in accordance with the first functional in Expression 2 should be maintained in an interval that is close to the maximum value and, at the same time, makes it possible to take into account the second part of Expression 2, i.e. to minimize the consumption of energy flows.

The Smart Complex control system, considered in the simulation performed, is shown in Figure 2. At that, we assessed the accuracy of predicting the total consumption of energy flows for two cases: (1) with the use of PID controllers and (2) with the use of fuzzy neural controllers.
The control system of Smart Object shown in Figure 2, is implemented on the basis of a controller taught both by error of the controlled object, $e_1$, and by errors $e_2$, $e_{A1}$ generated during the operation of the direct model ($A_1$), which acts as a reference.

The normalized ranges of values included in Expression 1 are listed in Table 1.

Table 1: Normalized ranges of Smart Object microclimate values

| Variables                                    | $S_{D1}(T_{dw}, T_{rw})$ p. u. | $S_{D2}(g_w, W_W)$ p. u. | $S_{D2}(\Phi_B)$ p. u. | $x_1(t)$ p. u. | $T_{ex}(t)$ p. u. | $g_{ex}(t)$ p. u. | $\Phi_{ex}(t)$ p. u. | $f_{ex}(t)$ p. u. | $x_1(t)$ p. u. | $f_{ex}(t)$ p. u. | $x_2(t + k)$ p. u. |
|----------------------------------------------|-------------------------------|---------------------------|-------------------------|----------------|-----------------|-----------------|-----------------|-----------------|----------------|-----------------|-----------------|
| 0.4                                          | 0.25                          | 0.25                       | 0.49                    | 0.25           | 0.25            | 0.75            | 0.4             | 0.75            | 0.5             |                 |
| 0.4                                          | 0.5                           | 0.5                        | 0.72                    | 0.4            | 0.5             | 0.78            | 0.49            | 0.81            | 0.5             | 6.5             |
| 0.4                                          | 0.88                          | 0.88                       | 0.75                    | 0.4            | 0.88            | 0.88            | 0.81            | 0.55            | 0.85            | 0.5             | 9.9             |
| 0.8                                          | 0.25                          | 0.25                       | 0.64                    | 0.8            | 0.25            | 0.77            | 0.59            | 0.88            | 0.6             | 5.6             |
| 0.8                                          | 0.5                           | 0.5                        | 0.76                    | 0.8            | 0.5             | 0.82            | 0.68            | 0.91            | 0.6             | 9.9             |
| 0.8                                          | 0.88                          | 0.88                       | 0.81                    | 0.8            | 0.88            | 0.87            | 0.78            | 0.77            | 0.7             | 5.7             |
| 1.2                                          | 0.25                          | 0.25                       | 0.68                    | 1.2            | 0.25            | 0.87            | 0.85            | 0.88            | 0.8             | 3.8             |
| 1.2                                          | 0.5                           | 0.5                        | 0.8                     | 1.2            | 0.5             | 0.9             | 0.89            | 0.94            | 0.9             | 5.9             |
| 1.2                                          | 0.88                          | 0.88                       | 1.2                     | 0.88           | 0.88            | 0.95            | 0.9             | 0.95            | 1.0             |                 |
If the Smart Object controller is based on the PID controller, the expression for the mathematical model to predict the parameters of total energy consumption can be repre

\[ P(t + 1) = 0.484 \cdot P(t - 7) + 0.387 \cdot P(t - 1) + 0.129 \cdot k(t) \]  \hspace{1cm} (17)

where \( P(t + 1) \) is the prediction for period \((t + 1)\); \( P(t - 7) \) is the actual energy consumption for period \((t - 7)\) before the prediction; \( P(t - 1) \) is the actual energy consumption for period \((t - 1)\) before the forecast; and \( k(t) \) is the meteorological influence indicator.

However, the significance of the above parameters is assumed at the level of averaged values [3,4], such as 75% for \( P(t - 1) \); 60% for \( P(t - 1) \); and 20% for \( k(t) \). These data can be interpreted as the probability of energy consumption forecast \( P(t + 1) \) on the indicated factors.

In Matlab, a unit with the multi-layer perceptron structure was used as a base for the simulated implementation of the reference model (based on artificial neural networks with the following parameters: the number of neurons in the hidden layer was 300; the sampling interval was 0.2 sec; the number of delay elements at the input was 2; the training sample was 1,500; the number of training epochs was 300; the training algorithm was train br.

The NFC settings are shown in Table 2.

| Table 2: NFC settings for Sugeno implementation of Smart Object control system |
|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| 1. Network type – NFC (Sugeno) |
| 2. Topology and implementation of fuzzy data input/output |
| Distribution of membership terms \( w_p \times T \times p \times v_z \) | Quantity of training rules | Types of transfer functions of input terms | Types of transfer function of output term \( x_1(f) \times x_2(f) \times x_3(f) \) |
| 16×16×16×16 | 45 | psigmf | linear |
| 3. Topology and training of artificial neural networks (multi-layer perceptron) |
| Quantity of layers (pcs) | Quantity of hidden layers (pcs) | Quantity of elements in training sample (pcs) | Quantity of elements in test sample (pcs) |
| 4 | 2 | 612 | 745 |
| Stopping condition – RMS Growth |
| ANN weights updating method – 500 epochs (free-scaled time period) |

The results obtained in the course of simulation for June and December 2018 are shown in Figures 3 and 4.
The obtained results indicate that the accuracy of FNC is higher than the performance of PID controllers at the considered periods, and hence FNCs can be a preferable solution for the tasks with poorly for malizable data that affect the operation of controlled object.

V. Conclusion

The article proposed a generalized optimization model has been proposed for a class of industrial and residential facilities, designed to satisfy consumer requirements for microclimate with a widely varying range of external factors and to minimize the consumption of energy resources. For that purpose, such utility systems
as heating, air conditioning/ventilation and illumination were considered, although it is possible to add other utility systems to the analysis.

The considered implementation of FNCs on the basis of fuzzy neural networks and artificial neural networks (reference models) is quite flexible and, therefore, applicable for poorly malizable factors. It gives FNCs advantages as compared to PID regulators in Smart Objects.

When assessing the energy consumption for maintaining the technological processes of heating, air conditioning/ventilation and illumination with FNC-based control systems, forecasting errors were reduced by 1.5–2.5% as compared to control systems based on PID regulators. If applied to Smart Objects, these algorithms can produce more efficient indicators by the real power loss criterion due to more accurate accounting of energy consumption in future periods.

Although initial investments into FNC-based control systems are 5–10% higher (as compared to control systems based on PID regulators), the payback period can be shorter due to visible economic effect.

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