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A Novel Machine Learning-Based Load-Adaptive Power Supply System for Improved Energy Efficiency in Datacenters

MICHAEL CHRYSOSTOMOU[1], (Student Member, IEEE), NICHOLAS CHRISTOFIDES[1], (Member, IEEE), AND DEMETRIS CHRYSOSTOMOU[2], (Student Member, IEEE)

[1]Department of Electrical and Computer Engineering and Informatics, Frederick University, 1036 Nicosia, Cyprus
[2]Department of Information Technology and Electrical Engineering, ETH Zürich, 8092 Zürich, Switzerland

Corresponding author: Michael Chrysostomou (st009893@stud.fit.ac.cy)

ABSTRACT Power Supplies are a key part of the modern Internet and Communications Technologies (ICT) industry. Modern Uninterruptible Power Supply (UPS) systems are modular and as such, consist of several Power Supply Units (PSUs). Even though various PSU designs are used to optimize operation efficiency at specific loading conditions they engender inefficient operation at other loading conditions. In order to optimize the energy efficiency in various loading conditions, this paper proposes a novel power supply multiplexing system engaging different combinations of PSUs which are controlled through machine learning techniques to maximize efficiency depending on the loading conditions. Each PSU combination is given a state number. Due to the vast number of combinations (states) that can occur in such systems and redundancy requirements, machine learning techniques are proposed. It is shown that by using the proposed novel system, an efficiency improvement of over 78% can be achieved in low loading conditions and an average 5.23% in all loading conditions.

INDEX TERMS Datacenter, machine learning, energy efficiency, power supply units.

I. INTRODUCTION

The vast and fast growth in the last decade of IoT, data processing, electric mobility and other energy consuming industries has led to a huge increase in the demand for power supplies [1]–[3]. Uninterruptible Power Supplies (UPS) are used to supply power for Internet and Communications Technology (ICT) equipment within datacenters or micro-datacenters to ensure quality and availability of power. ICT equipment are devices that can store and process data, such as servers, disc stations, data switches, transceivers etc., which are installed in infrastructures called datacenters. Datacenters of sizes up to one ICT rack are referred to as micro-datacenters.

In 2018, the global datacenter energy consumption reached a total of 205 TWh which was equivalent to 1% of the global electricity consumption [4] and it is projected that in 2030 this will correspond to around 3.8-12% of the global energy consumption [5]. Taking into consideration that the energy fed in a Datacenter is shared between UPS systems and Cooling systems [5], it can be easily deducted that the energy efficiency of UPS systems is of great importance. Back in 2011, the average energy losses of UPS systems could reach 18% [6] but modern state of the art UPS systems have efficiencies of over 90% for loads over 10% of full load [7]. The proposed system presented in this study shows that energy efficiency improvements of up to 78% can be achieved without compromising the security of supply. The comparatively lower efficiency of the power supplies in small loads is one of the key challenges for the datacenters today [8], [9], [5]. An ICT rack can have a power consumption from zero to 22 kW [10]. Furthermore, the load is not easy to predict since the power consumption depends on the CPU loading of the servers and other systems installed within the rack such as the number of equipment installed, the set cooling temperature and other parameters. Based on their application and power output level, power supplies can vary depending on their converter types and the switching devices used. A PSU in general has maximum efficiency at a specific load region.

Several research studies have been conducted for improving the energy efficiency of UPS systems. In [11], up to

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98.55% efficiency on 20% of loading has been shown. Alternative methods use novel dynamic range programmable PSUs where the high efficiency load region could be extended so as to have more than 90% efficiency from 5%-100% of loading conditions [12]. This has a compromise however in the peak efficiency (peak efficiency is 93.1% which is relatively low compared to PSUs that are optimized to work with specific loading regions).

Monitoring the parameters of a UPS towards improved efficiency and redundancy was proposed in [13], by changing the state of charge and other parameters of a UPS system. Optimized switching of internal, parallel power supplies that are incorporated in a server is proposed in [14]. Although it demonstrated great results in improving the efficiency of server systems, this solution has several limitations. For example, the server can only have a few power supplies, all power supplies in the server should be the same and the loading factor range is small compared to a whole datacenter. Activation and deactivation of different PSU modules in datacenters for energy efficiency improvement as a concept was introduced in [15].

Although a few years ago, datacenters used to work with Alternating Current (AC) UPS systems, datacenters now use DC 48 V UPS systems. This occurred after Facebook and Google announced the ''open compute project'' which proved that DC 48 V systems present better energy efficiency [16]–[18]. Load sharing between same size and type PSU systems, AC or DC, has been previously presented [19] and [20] but studies on load sharing between different in size and type PSUs has not been done up to date. Power Multiplexers have been recently used by TI to select the input between different types of power receptors for personal computers such as barrel-jack, USB cable, wireless charging etc. [21], but these are not related to energy efficiency improvements.

The novel concept of efficiency improvement by activating and deactivating combinations of unequal in size and type PSUs is presented in this work.

The main elements and contribution of the work are the following:

- Derivation of a new mathematical formula for load sharing of different type and size PSUs which is experimentally verified.
- The novel PSU Multiplexing system for improved efficiency. The proposed system activates those PSUs the combination of which presents maximum efficiency for the specific loading condition. For small loads for example, low power PSUs should be enabled and for larger loads, fewer but higher power capacity PSUs should operate in order to achieve maximum efficiency.
- The control strategy of the proposed PSU multiplexing system using machine learning techniques. The control strategy calculates the efficiency for different combinations of PSUs (states) and passes the information for maximum efficiency to the multiplexing system, maintaining at the same time the requirement for N+1, N+0 or N+N redundancy.

The remaining sections of the article are organized as follows. In section II of this work, the typical structures of UPS in datacenters are presented and the effect of loading conditions is analytically explained. The concept of PSU multiplexing is also elaborated. Section III provides the mathematical model for calculating the efficiency of a PSU and it is shown that load sharing between similar and dissimilar PSUs is related to the open circuit voltage and internal resistance of the PSU. In section IV, the mathematical model is experimentally verified. In section V the new PSU multiplexing concept is analyzed and in section VI, the machine learning algorithms are presented. Finally, the overall system performance is discussed in section VII where the energy efficiency improvement is evaluated.

II. EFFECT OF LOADING FACTORS ON PSU EFFICIENCY AND USE OF MULTIPLEXING TECHIQUES FOR EFFICIENCY IMPROVEMENTS

A. LOADING FACTORS AND ASSOCIATED EFFICIENCIES OF PSUs IN DATACENTERS

Due to the criticality of datacenters (storing and processing critical data); there is a high redundancy requirement for all stages. As a result, datacenters are categorized in Tier levels from 1-4 according to their redundancy capability. TIER III and TIER IV datacenters need redundant paths for all stages of the electrical and mechanical systems [22], [23]. Every stage of the installation for any fault or maintenance situation should have ''N'' capacity in kW (where ''N'' stands for ''Need''). The datacenter UPS systems are therefore designed with loading factors of 30-50% [8], for N+N (need plus need) or N+1 configuration case as shown in Fig. 1 and Fig. 2 respectively.

The loading factor of a PSU can directly affect the efficiency. This is mainly due to the structure of the PSU and the no-load loss of the power electronics converter circuits such as PSUs. It is uncommon and very rare for a system to have the same constant power consumption. Therefore, to be able to address and improve the overall energy efficiency of UPS systems in a micro-datacenter, the loading conditions in each instance must be considered.

For a N+N redundancy, the loading condition of the UPS is in fact close or under to 50%. For N+1 redundancy the loading condition can exceed 50% but then again, the loading factor is not constant. It can be shown from actual measurements that the workloads in ICT equipment can deviate by more than 45% [24]. ''Virtualization'' is a technique used to move workload from one ICT equipment to another in order to increase the loading factor and hence efficiency [10], [25].

In Fig. 3, a chart with the power consumption for 24 hours from an actual server system is shown. The server is installed in a datacenter of an ICT organization in Cyprus, serving office data storage. It can be seen that the load in a single server during a 24 h period can deviate by more than 34.8% (from 209 W to 321 W).

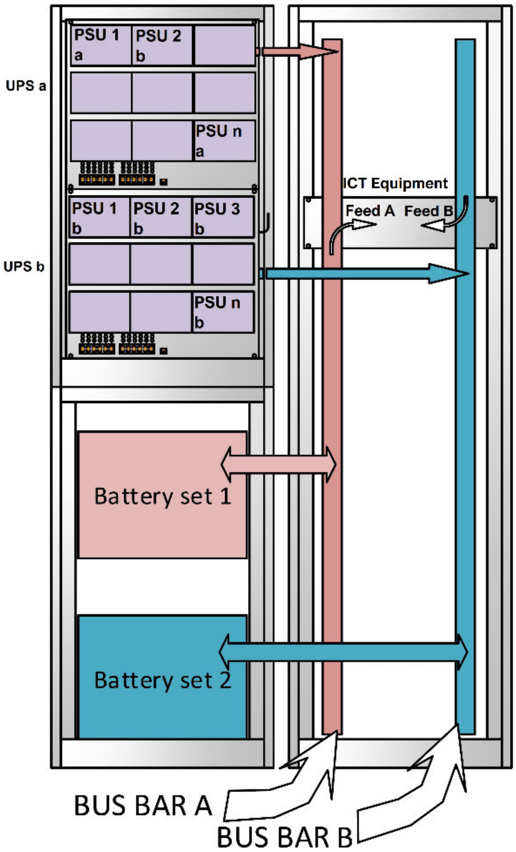

FIGURE 1. Typical N+N UPS datacenter configuration.

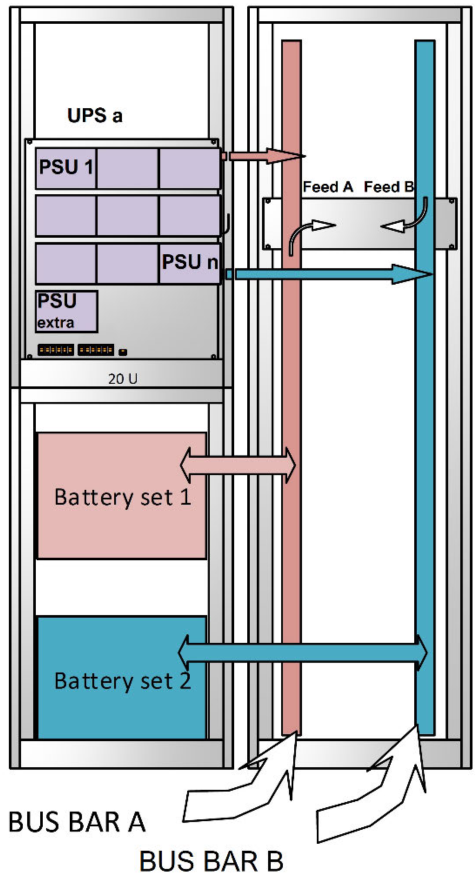

FIGURE 2. Typical N+1 UPS datacenter configuration.

B. THE NEW CONCEPT OF PSU MULTIPLEXING FOR DC UPS SYSTEMS

Multiplexing is a technique used in telecoms in order to send multiple signals or streams of information over a single communications link. Interpreting PSUs as multiple sources of power instead of information and considering the DC load bus as the single communication link, a PSU multiplexing can be used to select which and how many PSUs will be employed at any instant depending on the load.

The new concept of Power Supply Unit Multiplexing (PSUM) using multiple and different power supply units proposed in this work, aims at designing a highly efficient UPS system that can control redundancy levels of N+0, N+1 or N+N. Depending on the loading condition, different PSUs are activated or deactivated creating different states, representing combinations of different number and size of PSUs that are ON or OFF. The number of different states that a system with "k" similar PSUs can have is "k". A system with "y" different PSUs can have 2^y different states. Each state has a different energy efficiency performance for the same load output. Some of the states are measured, but due to the huge number of states that can be created, not all data are available for all states since it would necessitate enormous resources and time.

In order to be able to estimate the efficiency of different states, to identify the state that gives the highest efficiency

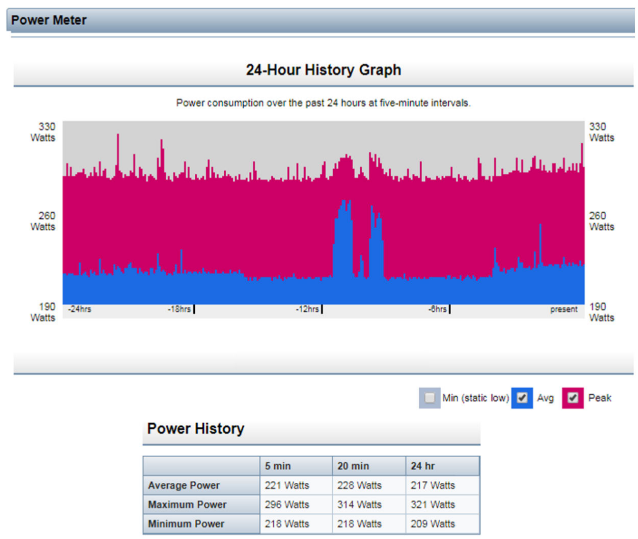

FIGURE 3. Power measurements on a HP ProLiant BL685c server.

at each load-instance and at the same time maintaining the redundancy levels required for every loading condition, the use of machine learning techniques is probably the ideal solution. The machine learning system is trained first through the measured data and then is used to estimate the efficiency of new states, identifying afterwards the best state that the system should operate to achieve the maximum possible efficiency under N+0, N+1 and N+N redundancy conditions.

III. MATHEMATICAL MODELING OF PSU POWER AND EFFICIENCY

A. RELATIONSHIP BETWEEN EFFICIENCY AND POWER OUTPUT

A basic block diagram of an AC to DC Power Supply Unit (PSU) is shown Fig. 4.

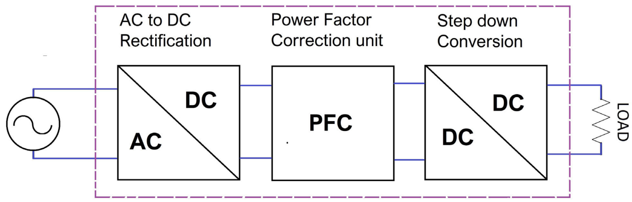

FIGURE 4. PSU circuit block diagram.

The power losses in the power supply system are calculated by the losses arising from the individual stages of the PSU such as the rectification stage, the PFC stage and the DC-DC conversion stage and are given by:

$$P_{total-loss} = P_{rec} + P_{pfc-loss} + P_{dc-dc\,loss} \tag{1}$$

Rectifier and PFC losses are given by [12]:

$$P_{rec} = 2 \cdot V \cdot f \cdot I_{in} \tag{2}$$

$$P_{pfc-L} = I_{sw}^2 \cdot R_{ds-On\,pfc} + I_{in-rms}^2 \cdot R_{ind} + P_{c.pfc\,loss} \tag{3}$$

$$P_{dc-dc\,L} = P_{sw-loss} + P_{trans-loss} + P_{ind-loss} + P_{cap} \tag{4}$$

$$P_{trans-L} = P_{tr-con-loss} + P_{no\,load\,loss} \tag{5}$$

where:

P_{rec}: power losses from the rectification stage

P_{pfc-L}: losses of the power factor correction stage

$P_{dc-dc\,L}$: losses of the DC-DC converter circuit

$P_{sw\,loss}$: MOSFET switch losses of the DC converter circuit (conduction and switching losses)

$P_{trans-L}$: transformer losses

$P_{ind\,loss}$: inductor losses

$P_{cap-loss}$: capacitor losses in DC-DC converter circuit

$P_{tr-con-loss}$: transformer load and frequency dependent losses

$P_{no\,load\,loss}$: transformer no load loss.

In order to identify the relation between input and output power in a PSU, all losses in the system are re-arranged to be given as a function of input and output power. Neglecting the switching losses in the DC-DC conversion part (due to ZVS strategies used in such converters) and after rearranging and expanding the equations, the efficiency and input/output powers are given as (6) and (7), shown at the bottom of the page, where [11]:

$$\mathrm{P_{tr-hysterisis}} = \mathrm{K_h \cdot V \cdot f \cdot B^n} \tag{8}$$

$$\mathrm{P_{tr-eddy}} = \mathrm{K_e \cdot V \cdot f^2 \cdot B^2} \tag{9}$$

where:

K_e *and* K_h are the eddy and hysteresis loss constants,

P_{eddy}: eddy current losses (W),

B: flux density *(Wb/m^2)*,

f: the frequency of the magnetic reversals per second (Hz),

t: core material thickness *(m)*,

V: core volume (m^3),

n: Steinmetz exponent ranging rom 1.5 to 2.5 depending on material.

V_{in}: input voltage to the PSU (V),

V_f: forward voltage drop on the input rectifier diodes,

t_{on}: MOSFET switches on-time (PFC circuit) (s),

f_{sw}: switching frequency of the PFC circuit (Hz),

$R_{ds-On\,dc\,out}$: MOSFETS on-resistance, DC-DC output stage (Ω),

R_{load}: load equivalent resistance in (Ω*)*,

$R_{ind-pfc}$: equivalent DC resistance of the PFC inductor (Ω),

$R_{tr.dc-dc}$: transformer equivalent DC resistance (Ω)

V_{boost}: boost PFC output voltage (V).

The losses in the switching devices and the magnetic copper losses are load dependent, while core losses are not load. Since the voltage at the load is kept within a specific voltage region (48-54 V DC), it can be concluded from (7) & (8) that core losses occur even at no load conditions. Inductor core losses are negligible compared to the winding (copper) losses. In transformers on the other hand, the core losses are higher

$$P_{out} = \alpha \cdot P_{in} + \beta \cdot P_{in}^2 + P_{no-load\,loss} \tag{6}$$

$$a = \frac{\left[1 - 2\frac{V_f}{V_{in}\cos(\varphi)} - t_{on}.f_{sw}\right]}{\left[1 + 2\frac{R_{ds-On\,dc\,out}}{R_{load}}\right]}$$

$$\beta = \frac{\left[\frac{R_{ind-pfc}+R_{ds-On\,pfc}}{V_{in}^2 Cos(\varphi)^2} + \frac{4R_{ds-On\,dc\,in}+2R_{ind\,dc-dc}+2R_{tr.dc-dc}}{V_{boost\,out}^2 Cos(\varphi)^2}\right]}{\left[1 + 2\frac{R_{ds-On\,dcout}}{R_{load}}\right]}$$

$$\mathrm{P_{no-load\,loss}} = \mathrm{P_{tr-hysterisis}} + \mathrm{P_{tr-eddy}} + \mathrm{P_{controller}} \tag{7}$$

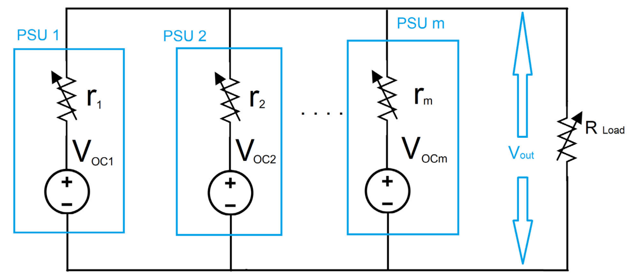

FIGURE 5. Equivalent simplified circuit of parallel PSUs connected to a common variable load.

because of the small number of winding turns in relation to the large core volume.

B. LOAD SHARING ANALYSIS

It can be theoretically and experimentally shown that using the same PSU type, size and brand, the load is shared between the number of parallel PSUs. For example, each PSU would supply 2 kW when four identical PSUs are connected in parallel to an 8 kW load. In large datacenters, modular UPS systems are used that consist of multiple PSUs working in parallel in order to gain redundancy and modularity.

The use of dissimilar PSUs, as well any kind of multiplexing strategy (as the one proposed in this work) is not used by any of the current system structures because of reasons that have to do with the security-of-supply. The proposed PSU multiplexing strategy does not affect the security of supply and significant benefit in the energy efficiency occurs. PSUs are voltage-controlled systems in which the voltage depends on the loading condition. A PSU system with higher open circuit voltage and lower internal resistance may provide more power to the load. The equivalent simplified circuit is shown in Fig. 5.

Using the equivalent circuit proposed in this work, the equation of output power as a function of output voltage, load and internal resistance can be derived for different PSUs and is given by:

$$P_{out-m} = \frac{(V_{oc-m} - V_{out})}{r_m} \tag{10}$$

For multiple PSUs it can be shown that connecting "w" number of PSUs of type A and "q" number of PSUs of type B in parallel supplying a common load, the voltage at the output is given by:

$$V_{out} = \frac{\left[w\frac{V_{oc1}}{r_1} + q\frac{V_{oc2}}{r_2} - P_{out}\right]}{\frac{w}{r_1} + \frac{q}{r_2}} \tag{11}$$

where: V_{oc1} is the PSU 1 open circuit voltage, V_{out} is the output voltage of the system, r_1 is the internal resistance of type 1 PSU and w & q are the number of PSUs of type 1 and 2 respectively connected to the system. The Power output of the system consisting of "w" PSUs of type A and "q" PSUs of type B is given by:

$$P_{out} = w \cdot P_{out1} + q \cdot P_{out2} \tag{12}$$

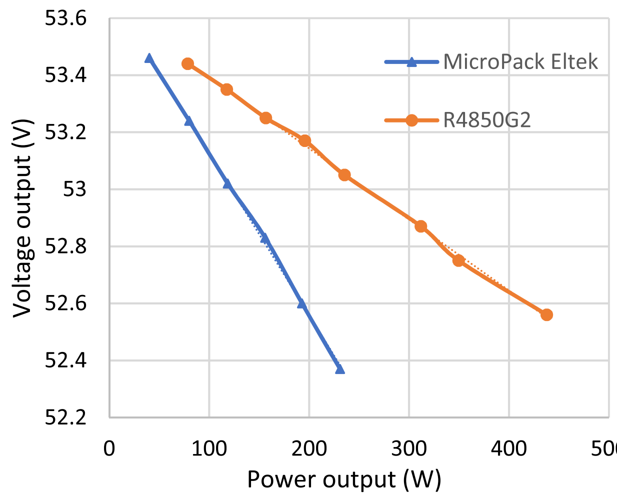

FIGURE 6. Output voltage vs. power output for micro-pack and R4850G2 PSUs.

It is obvious from (10), (11), and (12), that each of the PSUs, shares a portion of the output load based on the internal resistance, the open circuit voltage and the total load.

IV. EXPERIMENTAL VERIFICATION OF MATHEMATICAL MODELS

A. VERIFICATION OF RELATIONSHIP BETWEEN POWER AND OUTPUT VOLTAGE

The first part of the experimental set up was to prove that the relationship between output voltage and power is linear as given from (10). The linear relationship of output voltage and power can be verified experimentally as shown in the voltage vs. power output charts, Fig. 6, for PSUs R4850G2 and Eltek Valere Micro-Pack. The linear relationship of output voltage and power is due to the control system of the PSUs, whose main goal is to keep the output voltage of the PSU within specified range limits.

B. VERIFICATION OF RELATIONSHIP OF EFFICIENCY AND OUTPUT POWER

The next experimental set up was to measure the input and output power of single PSU units of types Eltek Valere Micro-pack and Huawei R4850G2 respectively in different loads, in order to derive the efficiency vs. power output, Fig. 7. As shown, the micro-pack has a higher efficiency than the R4850G2 for loads under 250 W but cannot supply greater loads. The R4850G2 has higher peak efficiency compared to the Micro-pack and a full load power output of 3 kW.

In order to verify the theoretical results regarding the system efficiency for a combination (states) of different PSUs, different set-ups where used. The experimental block diagram is shown in Fig.8.

Four PSU Eltek Valere micro-Pack modules and two Huawei R4850G2 PSUs are used in total. To verify the mathematical model, the open circuit voltage for each PSU was measured and the internal resistance calculated using a fixed load. Results are shown in Table 1.

TABLE 1. PSU measurements with no load.

PSU description	No load loss (W)	Open circuit Voltage (V)	internal resistance (Ω)
Huawei R4850G2	14.86	53.71	0.00349
MicroPack Eltek	4.91	53.68	0.00548

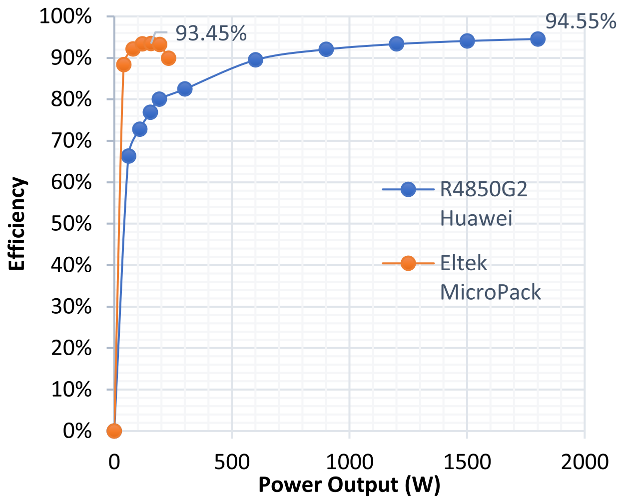

FIGURE 7. Efficiency vs. power of Eltek Valere micro-pack and Huawei R4850G2.

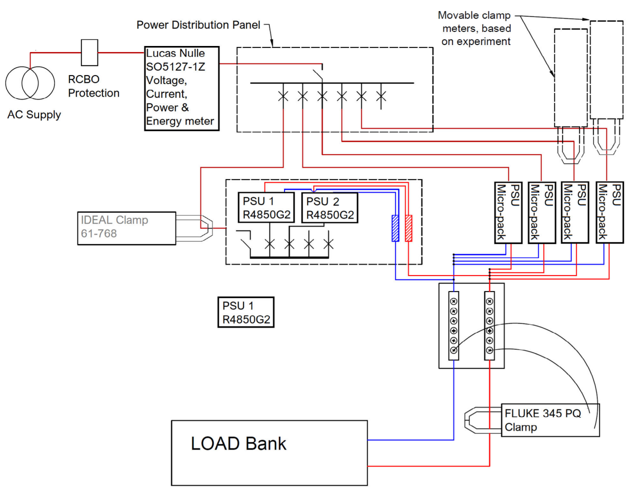

FIGURE 8. Block diagram of experimental verification.

Following this, the input and output current and voltage at different load levels was measured using combinations of 1-3 PSUs and efficiency levels are identified as shown in Table 2. For an output load of 156 W the highest efficiency is achieved with one PSU module. Comparing the case of three with two PSUs, it seen that the combination of three has a higher efficiency than the combination of two. It can be easily deducted that in each loading condition, a different PSU combination is required for optimal efficiency.

The same experiment was implemented using PSUs of type Huawei R4850G2. The results are shown in Table 3. Finally, an experimental setup was implemented to check load sharing between the different types of PSUs.

TABLE 2. Eltek Valere micro-pack efficiencies of 1–3 PSUs.

Pout 1 PSU (W)	Efficiency with 1 PSU (%)	Pout 2 PSU (W)	Efficiency with 2 PSU (%)	Pout 3 PSU (W)	Efficiency with 3 PSU (%)
0	0.00%	0	0.00%	0	0.00%
40.1	88.31%	39.82	77.18%	39.88	70.58%
79.97	92.13%	79.5	87.74%	79.41	83.41%
118.61	93.39%	122.81	90.97%	123.11	88.57%
156.06	93.45%	156.3	89.83%	156.41	89.89%
192.88	93.18%	193.61	88.81%	195.16	87.52%

TABLE 3. Huawei efficiencies of 1–2 PSUs.

Pout 1 PSU (W)	Efficiency with 1 PSU	Pout 2 PSUs (W)	Efficiency with 2 PSUs
0	0.00%	0	0.00%
39.7668	66.28%	39.72501	48.45%
78.61024	72.79%	78.6744	63.96%
156.71475	82.05%	156.92076	73.67%
195.87828	85.16%	235.9416	79.18%
235.542	85.03%	274.0617	81.08%
311.933	87.38%	311.6988	82.03%
349.7325	88.09%	350.3292	82.82%

Based on measurements taken using different modules and load sharing, the mathematical model is verified and a dataset of 36 states is built using different PSU combinations. Each state represents a number of PSUs to be activated from each type and represents a selection in the multiplexer. As stated previously, the number of states depends on the number of different PSUs.

The case study presented examines a datacenter with a 20 kW load. Two types of PSUs are used with however multiple numbers from each type. To maintain N+N redundancy where required, eighty 250 W Eltek Valere Micro-pack PSUs and another seven 3 kW R4850G2 PSUs are required. The total available UPS power would therefore be 41 kW, satisfying the N+N requirement. This combination of PSUs implies 560 different states (80 × 7). To prove the concept in the context of this work, only 36 states were created. The 36 states (combinations) are created empirically since the trend of efficiency against power output of each of the PSUs is known.

An optimal selection out of 560 states could lead to even better results in terms of efficiency improvement. As shown in Fig. 9, the experimental results verify the mathematical model with an error lower than 2% for loading conditions between 0-15% and lower than 0.5% for loading conditions between 15-100%.

V. PSU MULTIPLEXING TECHNIQUE

The efficiency of PSUs varies with load. Most PSUs present their highest efficiency in the loading region between 30-60%

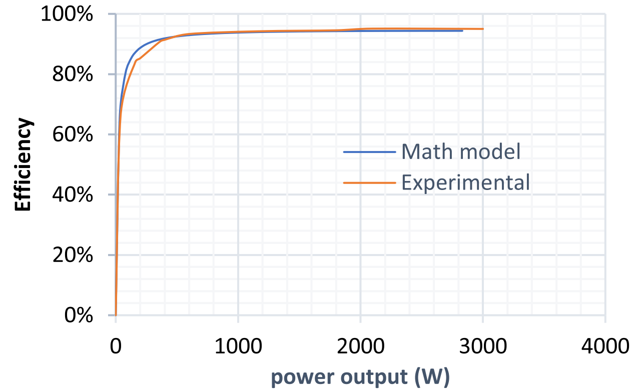

FIGURE 9. Experimental and mathematical comparison of efficiency vs. power output for R4850G2 PSUs.

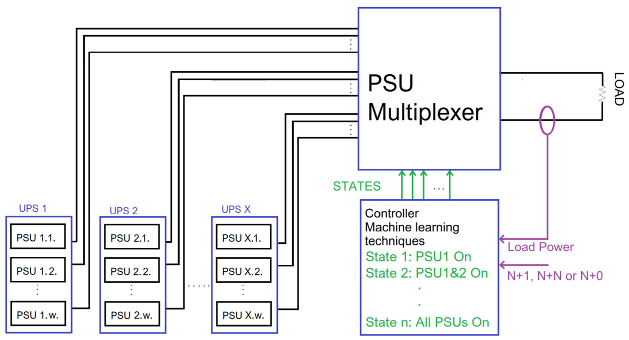

FIGURE 10. Proposed machine L. controlled PSU multiplexing system.

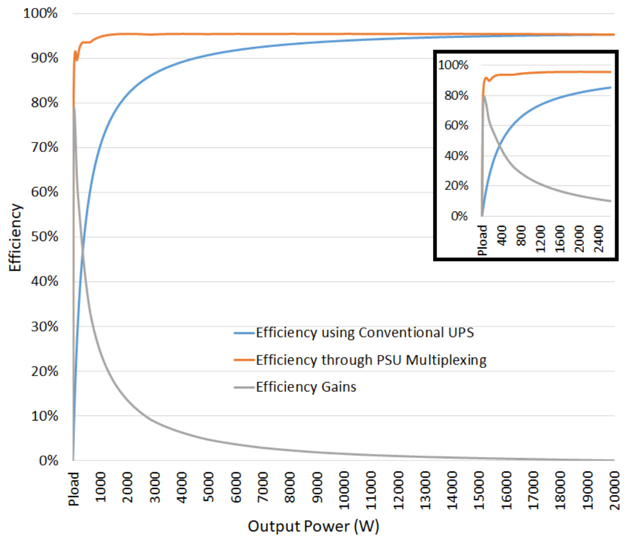

FIGURE 11. Efficiency vs. power comparison between standard UPS systems and the proposed PSU multiplexing ups system together with the efficiency gain (grey curve).

of full load as shown in Fig. 7. In typical datacenters today, the load is equally shared between multiple parallel PSUs in all loading conditions. In the proposed PSU multiplexing technique, individual PSUs are switched ON and OFF to achieve maximum conversion efficiency. The diagram of the proposed PSU Multiplexing system is shown in Fig. 10. A system with "y" same PSUs can have a number of y different states, but if a system has "y" different PSUs, the number of states can be created is 2^y. Each state has a different energy efficiency performance for the same load output.

A dataset with 36 different states and 4 UPS is built and fed to the machine learning system. As proposed in this work, multiplexing (i.e., selecting between different sources) of different PSUs leads to significant energy efficiency improvements. This can be seen in the projected efficiency vs. output power chart shown in Fig. 11.

Efficiency improvement of up to 78% can be achieved in very small loads and an impressive 13.62% efficiency improvement at around 10% of the 20 kW full load can be achieved with the proposed system, Fig. 11.

VI. MACHINE LEARNING

Changing between known states of PSU combinations to achieve maximum energy efficiency, could be easily done through optimization techniques without the need of machine learning algorithms. On the other hand, a single change in the dataset (such as a PSU malfunction or change of PSU parameters) could lead to overall system malfunction, since the mathematical model changes, if linear optimization control techniques are used. Furthermore, a PSU multiplexing system as proposed can have a huge number of different states. To be able to use optimization control systems, all efficiency states against load mathematical models should be evaluated. Changing a PSU type in the system, would lead to change of mathematical modeling in many states of the system. Therefore, with optimization models a change of a PSU model would need a change in mathematical formulation of a big number of states which is computationally expensive. In the contrary, changing a PSU model in a machine learning controlled system, would just need new data (measured data of efficiency against load) and re-training. Summarizing, machine learning techniques could be easily used in applications where adaptive control is needed such as in the proposed system.

The dataset used to train the model included actual measurements and calculated values based on (6) but are also comparable with manufacturers datasheets.

A. MACHINE LEARNING ALGORITHMS

1) CLASSIFICATION MODEL

When dealing with such a problem, a variety of machine learning algorithms can be applied. In this work, due to the non-linearity of the input/output relationship, linear models were avoided. The comparison of different algorithms is shown in table 4. As shown, the Random Forest (RF) classifier has the higher test precision, test recall and F1-score. On the other hand, the K-NN classifier requires significantly shorter training and prediction time compared to the other methods, with however, very similar test recall and test F1 score results in. K-NN is a non-parametric method which does not require training. A K-NN classifier assigns class

TABLE 4. Comparison of different classification algorithms.

Classification Method	Training Duration	Prediction Duration	Test Precision	Test Recall	Test F1
K-NN	0.006	0.021	0.9969	0.9904	0.9930
Extra Trees	1,973	0.173	0.9976	0.9936	0.9938
Random Forest	2,512	0.153	1	0.9968	0.9979
ANN with 2 Hidden L/s of 64 & 128 Neurons	12,949	0.603	0.9656	0.9646	0.9616
ANN with 3 Hidden L/s of 64, 128 & 256 Neurons	15,255	0.582	0.9528	0.9518	0.9495

membership based on neighbor plurality votes. Then, K-NN regression obtains the k nearest neighbor average output value. One of the key strengths of the K-NN algorithm, is its ability to constantly adapt to new data, which leads to easy adaptability to multi-class problems like the current case. In the contrary, due to its no training characteristic, this algorithm can become slow as data increases.

Although RF algorithm requires training, it can be faster in later predictions. RF is an ensemble method, using multiple decision trees and averaging their predictions. This usage of multiple decision trees improves the accuracy of the prediction and avoids overfitting. Moreover, RF can work well for both categorical and continuous values, which is an expectation in this case, given the categorical redundancy input feature, and continuous efficiency feature. Besides that, similar to K-NN, RF can be easily applied on multi-class classification problems. In the contrary, the RF algorithm is computationally complex during training, since requires creation of numerous decision trees.

Therefore K-Nearest Neighbor (KNN) and Random Forest (RF) techniques proved to be the best solutions for the PSU Multiplexing problem. The model is designed with two inputs and two outputs.

The inputs are:

- The power output level of the load
  - $P_{Load} \in \mathbb{R}_+$
- The redundancy input
  - 0,0 – No redundancy
  - 0,1 - N+1 redundancy
  - 1,1 – N+N redundancy

The outputs are:
- The state selection based on the load
- The efficiency of the state in the specific load.

The two outputs were dealt by two different models, one performing multi-class classification (state output) and one performing regression (efficiency output).

For the supervised classification task, by performing the non-parametric method K-NN with 5 neighbors, an average precision of 98.81% was achieved, a recall of 98.34% and an F1-score of 98.44%. Moreover, a classification accuracy of 98.34% was achieved.

TABLE 5. Comparison of different regression algorithms.

Regression Method	Valid/on Standard Deviation	Validation MSE	Training Duration	Prediction Duration	Test MSE
K-NN	0.0046	0.00087	0.002	0.004	1,762 E-06
Random Forest	0.0001	0.00003	7449	0.329	5.258 E-07
ANN with 2 Hidden Layers of 64 & 128 Neurons	0.3449	0.16213	8868	0.191	2.475 E-05
ANN with 3 Hidden Layers of 64, 128 & 256 Neurons	0.3290	0.14453	27991	0.415	7.149 E-05

Finally, applying the random forests method, which utilizes the strengths of decision trees and avoids overfitting, the outcome can be improved drastically. The classification accuracy when using random forests classifier can reach 99.34%, while the average precision, recall and F1-scores reached values of 99.38%, 99.34% and 99.34% respectively. The number of estimators used within our model where 1000 and were chosen using cross-validation.

2) REGRESSION MODEL

The comparison of different regression algorithms is shown in Table 5. As shown in Table 5, RF and K-NN regressors have significantly lower validation standard deviation, and test Mean Squared Error (MSE) values compared to Artificial Neural Networks (ANN). Despite RF regressor has significantly higher training duration time compared to K-NN, it has lower MSE.

Using the supervised regression task and performing the non-parametric method K-NN with 5 neighbors (chosen using cross-validation) a score of 96.7% R^2 and a MSE score of 3.88 e-06 was achieved with one case of efficiency prediction error higher than 1% ($\Delta e = 3.15\%$). On the other hand, using random forests regressor with 1000 estimators the score was improved to 99.59%, the MSE score was improved to 4.87 e-07 and the efficiency miss-match was in all cases lower than 1%.

3) FINAL MODEL SELECTION

Both the regression and classification algorithm models can achieve great results that could be used to choose the best state in which the system should operate and predict the expected efficiency. Although the K-NN method does not need to be data-trained, random forest models appear to give better results which are however computationally more expensive during training. However, in real time applications, a trained random forest algorithm model should be faster than K-NN which needs to run through all available data. Therefore, our

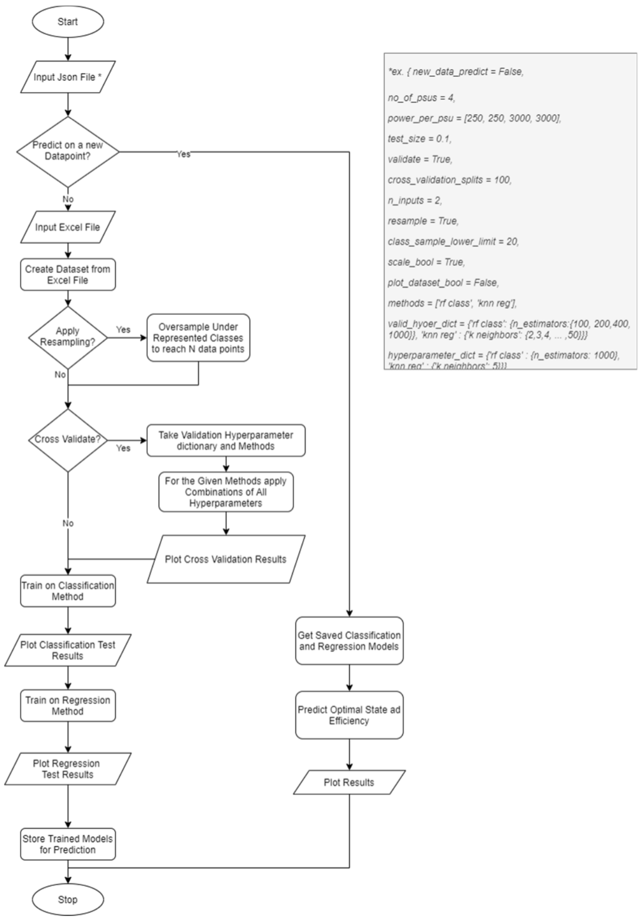

FIGURE 12. **Flow chart of the machine learning main program.**

final model was chosen to include the random forest classifier for the state choice, and the random forest regressor for the efficiency prediction.

The flowchart of the implemented main code of our machine learning program is shown in Fig.12.

B. DATA PREPROCESSING

The data pre-processing necessitates initial evaluation of the representation of each class within the dataset. The analysis of the data showed that some of the states might be under-represented, while other cases might be over-represented as illustrated in Fig. 13. For example, state 36, is presented in more than 20% of cases that show optimal efficiency, while state 2 for example is represented in less than 1% of cases.

However, balancing between state representation, should be avoided since the under-represented states also represent less observed high efficiency cases. Moreover, the increased representation of states that are optimal at higher P_{Load} values are more frequent due to the fact that power supplies tend to have higher efficiency in loading conditions of 30-60% of full load and therefore large size power supplies have a larger representation of power output in this region. Additionally, those few under-represented and over-represented states accumulate a minority of the possible states represented in the dataset.

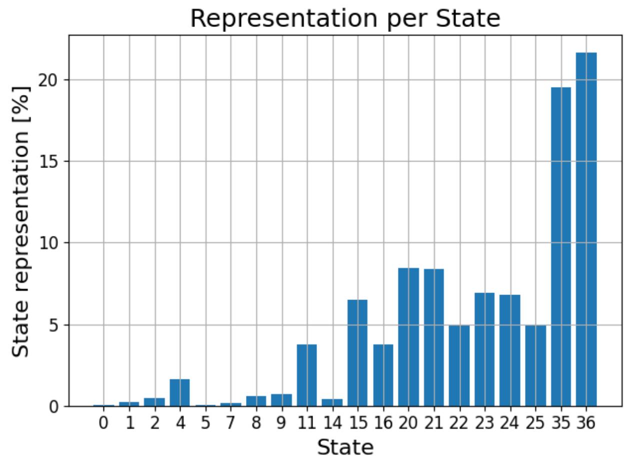

FIGURE 13. **State representation chart. In this chart is shown the percentage that each of the 36 states showed optimal efficiency. i.e., state 22 had optimal efficiency for 5% of the time.**

FIGURE 14. **No redundancy case, most efficient state per load.**

The dataset was split in a training set and a test set. The latter was chosen by randomly sampling 10% of the existing data. The training set consisted the remaining data. Moreover, due to the nature of the inputs, where P_{Load} can achieve higher values compared to the discrete values of the redundancy input, standardization was performed which ensured zero mean and unit variance of each feature. This measure, although it can theoretically be skipped for random forests classifiers and regressors, it was kept within the implementation as it is not harmful and helpful for the machine learning problem solution.

C. MACHINE LEARNING MODEL RESULTS

As stated previously, the machine learning model solves the optimization problem based on 3 options in terms of redundancy, namely N+1, N+N and No redundancy (N+0) cases. The results for no redundancy case are shown in Fig. 14.

The system uses 12 different states to have optimized efficiency from 0-20000 W. It can be easily seen that efficiency of the UPS system is above 95% for all load conditions above1200 W, and above 92.5% for loads above 40 W. The efficiency gains are shown in more detail in Fig. 11.

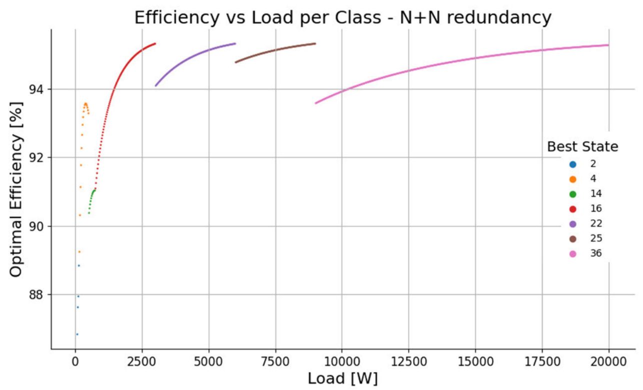

FIGURE 15. N + 1 redundancy case, most efficient state per load.

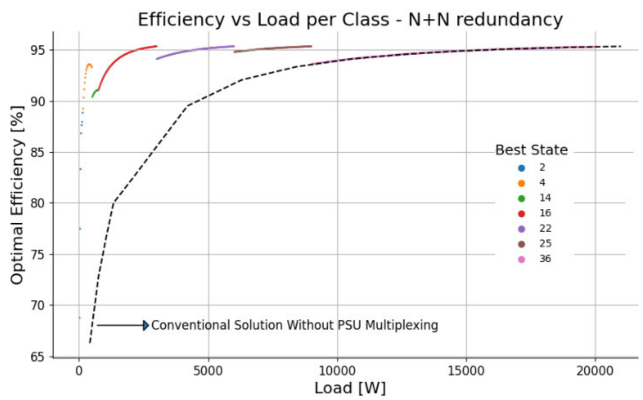

FIGURE 16. N + N redundancy case, most efficient state per load.

The optimized solution of the PSU Multiplexing, with N+1 redundancy is shown in Fig. 14. The system is using 12 different combinations of PSUs (States) to achieve maximum efficiency of conversion and at the same time keep N+1 redundancy. As shown in Fig. 15., the efficiency in N+1 optimized PSU Multiplexing solution, is above 95% for all loads above 2000 W (10% of full load).

The solution of N+N redundancy case can be seen in Fig. 16. It is obvious from the chart, that only 7 states are changing in N+N optimized efficiency solution, but the efficiency of conversion for optimized N+N is lower than optimized N+1 and N+0 cases. The efficiency of conversion of N+N case with the optimized PSU Multiplexing system, is higher compared with the conventional system solution (Without PSU multiplexing) for all loads between 0-9000 W (i.e. 0 to 45% of full load).

VII. CONCLUSION

This work proposes a novel system with a PSU Multiplexing technique using machine learning algorithms that improve the efficiency of conversion in a DC UPS system by maintaining the required redundancy of the power supply. Different PSUs are measured experimentally and characterized in terms of efficiency against load and a mathematical model is built to give efficiency values of different PSU combinations. Each PSU combination is represented by a state and each state has a different efficiency performance in a given load power output. The PSU multiplexing controller using machine learning techniques, identifies the ideal state for each load. It is shown that an efficiency improvement of up to 78.9% can be achieved for loads of about 40 W compared to existing PSU systems without multiplexing. Furthermore, a 24.52% efficiency improvement can be achieved for loads of 1 kW, a 13.62% for loads of 2 kW and an average efficiency improvement of 5.23%. for all loads. Taking into consideration that modern datacenters use modular UPS systems (with multiple PSUs), the cost to include multiplexing in the existing systems is negligible. A 5.23% energy saving is a significant improvement considering that datacenters consume about 1% of the annual global energy. Finally, the new system can also be applied in other AC to DC power supply systems such as in the electric vehicle industry (electric chargers). If the proposed system is applied in older UPS systems with lower efficiency PSUs, even better results may be achieved.

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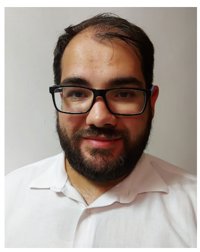
MICHAEL CHRYSOSTOMOU (Student Member, IEEE) was born in Nicosia, Cyprus, in 1983. He received the B.Eng. degree in electronic and electrical engineering and the M.Sc. degree in sustainable electrical power from Brunel University London, U.K., in 2006 and 2007, respectively. He is currently pursuing the Ph.D. degree with the Department of Electrical Engineering, Frederick University, Cyprus. From 2007 to 2009, he joined Conergy AG, Cyprus branch, as an Electrical Engineer and then as the Head of the Photovoltaic Department at the same company. In 2009, he joined EPIC Ltd. as an Engineers' Supervisor and the Environmental Management Representative. In 2016, he was promoted to the position of Power and Datacenter Planning Manager and worked there until September 2019. Currently, he works with the Ministry of Education of Cyprus. He is approved from Uptime Institute as an Accredited Tier (Datacenter) Designer (ATD), and from CNET and Pearson Education as a Core Datacenter Management Professional (CDMP®). He is also registered in IRCA as an Environmental (ISO14001) Lead Auditor. His current research interests include power electronics, renewable/sustainable electrical energy, and datacenters. He is a member of the Cyprus Technical Chamber (ETEK) in electrical engineering, and the Electromechanical Services (EMS).

NICHOLAS CHRISTOFIDES (Member, IEEE) received the B.Eng. degree in electronic and electrical engineering from the University of Birmingham, U.K., in June 1999, and the master's and Ph.D. degrees in electrical power engineering from The University of Manchester Institute of Science and Technology (UMIST), in September 2000 and December 2003, respectively, he pursued the Ph.D. degree following the successful completion of his thesis entitled "On-Line Partial Discharge Monitoring in Belted Paper-Insulated Medium Voltage Cables." He joined the Electrical Engineering Department, Frederick University, Cyprus, in October 2006. His main research interests include energy sustainability and power quality, performance assessment, and lightning protection of photovoltaic systems. He is also registered as an Electrical Engineer with the Electromechanical Service, Ministry of Communications and Works, and a Certified Government Specialist for the energy efficiency categorization of residential and non-residential buildings. He has been carrying out consulting work, since 2005, on electrical photovoltaic system designs and participates in various committees. He is a member of the Cyprus Scientific and Technical Chamber (ETEK) and the Institution of Engineering and Technology, U.K. (IET).



DEMETRIS CHRYSOSTOMOU (Student Member, IEEE) was born in Nicosia, Cyprus, in 1994. He received the bachelor's degree in electrical engineering from the University of Cyprus, in 2018, and the Master of Science degree in robotics, systems, and control from ETH Zürich, in 2021. From 2015 to 2018, he was an Research Assistant at the Power System Modelling (PSM) Laboratory, University of Cyprus. In 2020, he worked as a Research and Development Intern at ABB Switzerland. His main research interests include machine learning algorithms and artificial intelligence, robotics, and electric power and energy. He participated as a member of External Evaluation Committee Cyprus Agency of Quality Assurance and Accreditation in Higher Education (CYQAA).