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INCREASING ENERGY EFFICIENCY OF QUASI-RESONANT CONVERTERS UNDER DYNAMIC LOADS BY MEANS OF ADAPTIVE AI CONTROL AND SIMULATION

The article investigates the problem of increasing energy efficiency and ensuring the stability of quasi-resonant switched-mode converters (QRC) under dynamically changing load conditions. The operating circuit and loss calculation formulas have been selected. A comparative analysis of modern simulation environments was performed to improve real-time control algorithms. The feasibility of integrating artificial intelligence tools, particularly reinforcement learning (DRL) and large language models (LLMs), is analyzed.

Keywords: *quasi-resonant converter; zero-current switching; adaptive control; hardware-in-the-loop simulation; artificial intelligence; reinforcement learning; large language models; energy efficiency.*

Figures: 2. Tables: 6. References: 19.

Relevance of the research. Modern switched-mode voltage converters require high energy efficiency and adaptive control under dynamically changing loads while minimizing electromagnetic interference. QRC with soft-switching modes significantly reduce switching losses, allowing for increased PCE and raised switching frequency. For example, switching power switches at zero current allows for significantly minimizing switching losses. In combination with ultrafast GaN/SiC transistors [1], which have switching periods measured in nanoseconds, this enables operation at high frequencies. High frequency and dynamically changing operating modes create new challenges. Rapid changes in operating modes can generate high-frequency oscillations and require fast and adaptive control. This problem can be addressed by means of adaptive control using machine learning and modern large language models (LLM) [2].

Target setting. The key problem is ensuring the stable and energy-efficient operation of QRCs under conditions of dynamically changing loads. The quasi-resonant operating mode significantly reduces the switching losses of the power switch. However, when operating with dynamically changing loads, electromagnetic interference may arise, energy losses may increase, and system stability may decrease. Modern GaN/SiC transistors with switching times measured in nanoseconds allow for operation at ultra-high frequencies. Classical control methods may reduce energy efficiency during dynamic load changes. Therefore, flexible control methods are necessary - for example, adaptive control using machine learning and modern LLMs.

Actual scientific research and issues analysis. Recent publications indicate that LLMs and other AI methods are already being applied in power electronics. In one publication, GPT-4 with a Retrieval-Augmented Generation (RAG) mechanism [3] was able to automatically select a DC-DC converter topology, calculate parameters, and generate code for functional blocks (e.g., an MPPT block in Simulink) [4]. Two GPT agent copies were configured: one selected the optimal circuit, and the other selected components and program code according to given technical specifications. The results showed that ChatGPT is capable of independently constructing control algorithms and explaining its decisions based on technical data.

In the publication by Bernadić, A., author built an agent based on LLaMA 3 in the Pandapower environment for grid control and found that integrating LLMs significantly improves the efficiency and reliability of the power system operation. The authors note the potential of language models for grid stabilization. Another example is the specialized model PE-GPT, an LLM trained on power electronics, which outperformed human experts by 22.2% in decision accuracy and standard GPT-4 by 35.6%. These experiments testify that LLMs already act as "intelligent assistants" in designing converters, optimizing parameters, and formulating control algorithms [5].

Existing publications by foreign and Ukrainian authors lack a detailed comparison of available software environments and the language models available for integration with them. However, there is a need for such a comparison, as there are dozens of different software environments and language models. Most of these solutions are paid, and it is important to select the software environment, machine learning package, and language model in accordance with the set goal.

The aim of the research is a comprehensive study of integrating modern AI solutions, namely large language models and deep reinforcement learning, into control systems for switched-mode converters to enhance energy efficiency and eliminate electromagnetic interference. The objective is to provide a detailed description and comparison of various language models, assessing their suitability for controlling QRCs. Available software environments and their integration with language models and machine learning are examined. As a result of the research, the optimal solution for this task is selected, and a plan for further research is formulated.

The statement of basic materials.

Figure 1 shows the model of a parallel QRC-ZCS, and Figure 2(a) shows the timing diagrams of its operation in the case of operation without diode VD3. Analysis of the circuit operation allows distinguishing five characteristic switching intervals of the QRC-ZCS, which include [6]:

1) VT turn-on interval (t0-t1): The beginning of the cycle when the power switch starts conducting current.

2) VT on-state interval (t1-t2): The main conduction phase when current flows directly through the transistor channel.

3) VT on-state interval via diode (t2-t3): The stage of the resonant process when the current changes direction and closes through the reverse (anti-parallel) diode D0.

4) VT turn-off interval (t3-t4): The process of turning off the transistor when the current passes through zero (ZCS).

5) VT off-state interval (t4-t0): A pause in the operation of the power switch, when the energy stored in the main inductor L is transferred to the load [6].

For this model, these physical stages correspond to the following time ranges on the oscillograms: 1-2; 2-4; 4-6; 6-7; 7-1. These timing diagrams demonstrate that parasitic high-frequency oscillations, caused by resonant phenomena between circuit elements and parasitic capacitances, do not have time to cease before the arrival of the next control pulse.

The presence of undamped oscillations in the fifth switching interval is a problem requiring a solution. This leads to additional losses in the converter due to the dissipation of parasitic oscillation energy on the active resistances of its elements. It is important that the output voltage regulation in the QRC-ZCS is carried out by means of pulse-frequency modulation (PFM). Therefore, if this converter operates in modes where the duty cycle exceeds the threshold value of 0.2, there is a high probability that the power switch will start opening at a moment when the current in the circuit is not equal to zero. This leads to a violation of soft-switching conditions and a sharp increase in energy losses in the power switch. An effective solution to this problem is modifying the circuit and connecting an additional diode between the drain of the power switch and the load. In such a circuit, parasitic oscillations will decrease practically to zero.

Timing diagrams of the operation of such a converter with the introduced diode are shown in Fig. 2(b). In this figure, the process dynamics have changed, and the five characteristic switching intervals of the QRC-ZCS described above now correspond to new time ranges: 1-3; 3-5; 5-7; 7-8; 8-1 [6].

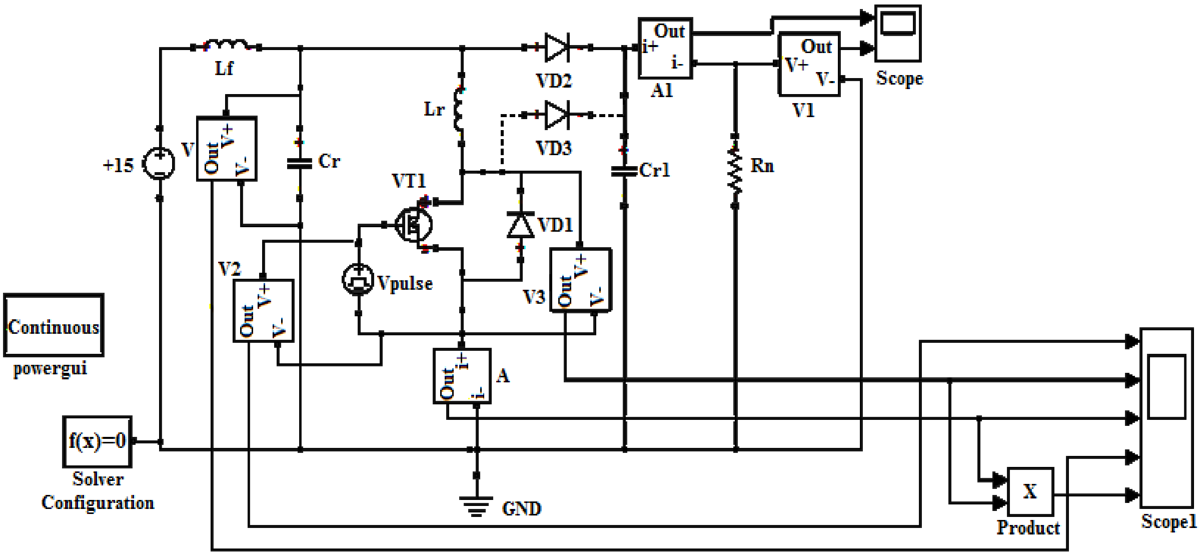

Fig. 1. Model of a parallel QRC-ZCS

Source: [6].

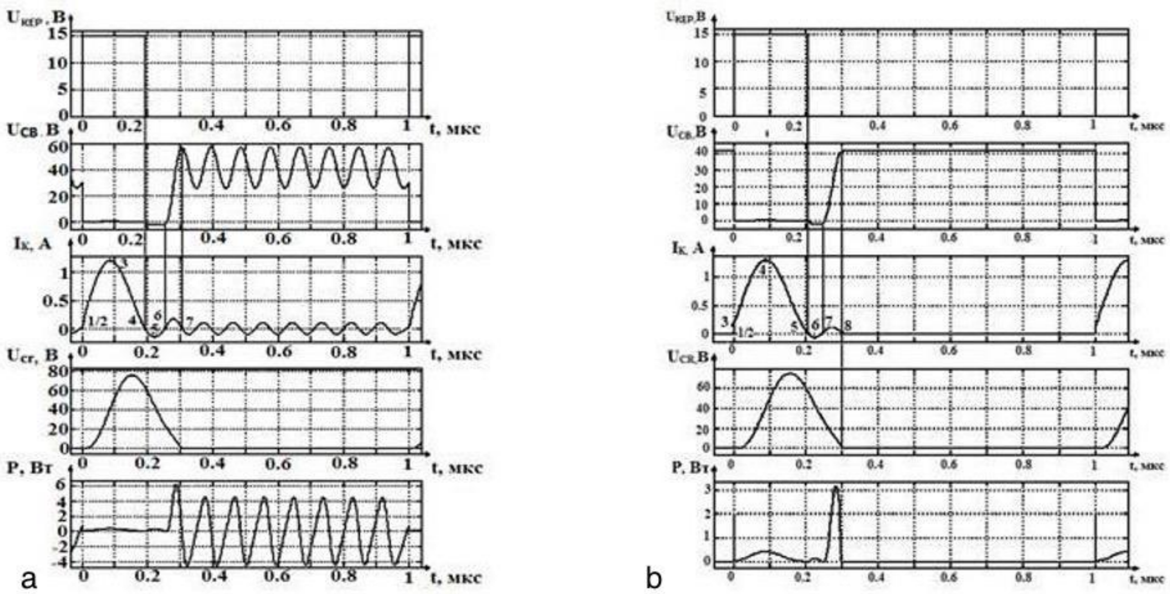

Fig. 2(a) - shows the timing diagrams of the QRC-ZCS operation without diode VD3. Figure 2(b) - illustrates the operation of the improved converter with the additional diode VD3.

Source: [6].

For the quantitative assessment of energy efficiency, a boost converter model is used. The calculation of total losses in power switches for both the QRC-ZCS and the traditional PWM converter is carried out by summing the losses in each separate switching interval. At the same time, losses in the last interval can be neglected, since the switch is in the closed state, and the leakage current is close to zero. The loss calculation is presented in Formula 1.

$$P_n = \frac{1}{t_n - t_{n-1}} \int_{t_{n-1}}^{t_n} u_{ds}(t) \cdot i_{VT}(t) dt \tag{1}$$

The power dissipation at each stage is determined as the integral of the product of the instantaneous values of the drain voltage Uds - drain-source voltage - and the channel current Ivt - current through the power switch over the duration of the switching interval n. An even more accurate criterion is the estimation of the total energy losses in the power switch per cycle.

This indicator is calculated by integrating the instantaneous power function over time for each interval. The loss calculation is presented in Formula 2.

$$P_n = \frac{1}{t_n - t_{n-1}} \int_{t_{n-1}}^{t_n} u_{ds}(t) i_{VT}(t) dt \qquad (2)$$

Having defined the mathematical formulas for calculating energy losses, the next step is to address the challenge of increasing power density and enhancing energy efficiency across various load levels of the power switches. PWM converters suffer from switching losses caused by the simultaneous presence of high voltage and current on the power switch during switching transients. These losses tend to increase as the frequency rises. To address this issue, it is possible to combine existing control methods with novel control approaches based on AI and machine learning. This approach can improve the energy efficiency of voltage converters under dynamically changing loads.

Selecting the appropriate simulation platform is crucial for obtaining reliable and reproducible results, especially when working with high-frequency and nonlinear systems such as QRCs. Software environments capable of simulating an experimental model serve as a vital tool for implementing AI-based adaptive control. Such environments enable topology verification, control algorithm development, and parameter analysis for the subsequent creation of physical prototypes.

The MATLAB/Simulink platform by MathWorks is a popular tool for modeling and control system development. For power electronics modeling, the Simscape Electrical software environment is used. It allows for the creation of physical models of electrical, mechanical, thermal, and other systems. For advanced modeling of DC-DC converters, the Simscape Electrical Specialized Power Systems toolbox is often utilized, ensuring high accuracy [7].

The MATLAB platform features built-in toolboxes such as the Deep Learning Toolbox and Reinforcement Learning Toolbox. Adaptive control of QRCs is a task that MATLAB can execute using machine learning. The switched-mode converter model in Simulink/Simscape can be used as an environment for training a DRL agent, which learns to control the switch energy-efficiently, replacing traditional PID regulators or complex fuzzy logic systems [8].

A drawback of such a system is the simulation speed. Due to the use of detailed models and differential equations (e.g., ode45, ode15s), modeling switching circuits with high frequencies and parasitic capacitances may require significant computational power. MATLAB version R2024a features an improved Reinforcement Learning Toolbox supporting DQN, PPO, SAC, and DDPG algorithms. These agents can learn to control QRCs within the Simulink environment [9].

MATLAB has integration with Python, interaction with Large Language Models (LLMs) becomes possible. LLMs can be used to automatically generate new code or improve existing code and scripts for configuring complex simulations in Simulink, which can accelerate research.

The PLECS software environment by Plexim GmbH [10] is a software package developed for power electronics simulation. Its key advantage is speed. Unlike Simscape, which uses complex nonlinear semiconductor models, PLECS uses idealized switch models that neglect parasitic parameters (less than 10 ns). This provides a significant advantage in simulation speed specifically for switched-mode converters. Losses are described analytically, allowing for a quick estimation of efficiency. This solution is advantageous during the initial stages of research.

The PLECS software environment exists in two versions. PLECS Blockset integrates directly into the Simulink environment. This allows modeling the control system in Simulink and the power circuit in PLECS. Moving the entire control system from Simulink into the PLECS block can increase simulation speed. The PLECS Standalone version is an independent environment that does not require MATLAB/Simulink and provides even higher speed.

Integration with AI is limited. PLECS does not have its own built-in AI tools. However, it can interact with Python scripts, allowing for the import and execution of neural networks. This integration is implemented through the simulation architecture: a DRL agent implemented in Python calls the PLECS simulation via an API script or through third-party tools such as PyPLECS [10].

A disadvantage of this software environment is lower computational accuracy compared to MATLAB. Due to object idealization, speed increases, but result accuracy decreases.

The OpenModelica software environment [11] is a free, open-source platform based on the object-oriented, declarative language Modelica. In Modelica, instead of defining signal flows, the user describes the system through its physical components and mathematical equations. This allows for easy description of complex and composite systems. As open-source software, it is free and offers complete transparency - the user can see the equations underlying each block. This solution is also well-suited for developing control algorithms and optimization.

The Modelica software environment can be integrated with LLMs, where LLMs generate and modify Modelica code. This makes Modelica a promising platform for AI-assisted workflows, where the user and AI collaborate on the textual description of the model [11].

Table 1 – Comparison of simulation software environment characteristics

Parameter	MATLAB/Simscape R2025b	PLECS 4.8	OpenModelica 1.25.5
Modeling Paradigm	Multi-domain physical modeling. Based on solving nonlinear differential equations (ODE).	Modeling based on idealized switches. Avoids solving nonlinear ODEs by treating switches as ideal components with linear states (on/off).	Declarative modeling. Based on solving differential-algebraic equations (DAE).
Parasitic Parameter Handling	High accuracy. Detailed modeling of nonlinearities, thermal parameters, SPICE model import.	Idealized. Neglects parasitic parameters with small time constants (< 10 ns).	High accuracy (Determined by the level of detail in DAE equations).
Speed for QRC Systems	Low/Medium (Computationally complex due to solving nonlinear ODEs).	Very High (Optimized for switching circuits, 10-20 times faster than nonlinear models).	Medium (Depends on DAE system complexity and solver efficiency).
Integration with Machine Learning	Yes. Reinforcement Learning Toolbox (DQN, PPO, SAC, DDPG).	No. Requires additional simulation via Python API.	No. Requires additional simulation via API.
Integration with LLM	Script generation (.m).	Script generation (Python).	Highest suitability, ability to generate control code.

Source: [7-11]

If modeling in software environments confirms the working control system model, the next step is verification using a physical controller. This process is called Hardware-in-the-Loop (HIL) simulation [12]. In a HIL system, the real hardware controller is connected to a real-time simulator that acts as the power stage of the switched-mode converter. This allows for safe verification of the controller's operation in thousands of scenarios, including emergency ones, without the risk of damaging expensive equipment. Selecting the appropriate HIL platform is an important decision that affects simulation accuracy, testing throughput, and the final simulation result.

The most popular HIL simulators for power electronics are Opal-RT Technologies, Typhoon HIL, National Instruments, dSPACE, and Speedgoat. These simulators are often used for the development of modern electric vehicles and the integration of renewable energy sources.

Opal-RT specializes in high-performance real-time simulators combining powerful multicore processors (CPU) and advanced FPGAs, specifically AMD Kintex-7 and Virtex-7. For power electronics modeling, Opal-RT developed the specialized eHS simulator. This high-level simulator allows for modeling complex converters directly on the FPGA, achieving small simulation steps. Such a simulator has high performance, which is important when modeling QRCs operating at high frequencies. Opal-RT platforms, such as OP5707XG2 or OP4512, thanks to eHS and FPGA with high timer resolution (up to 625 ps with oversampling), achieve simulation steps down to 90–145 ns. This allows modeling switching frequencies up to 500 kHz and is one of the few solutions on the market capable of modeling controller operation using high-frequency QRCs based on SiC and GaN.

The central processor is based on Intel Xeon Gold processors and is offered in two configurations: OP5707XG2-08 (P/N 429-0307): 8 cores with a clock frequency of 4.2 GHz. OP5707XG2-16 (P/N 429-0310): 16 cores with a clock frequency of 3.9 GHz.

In this case, the 8-core configuration with a higher clock frequency (4.2 GHz) is optimized for reducing latency and minimizing the time step for single-thread simulations performed primarily on the CPU. At the same time, the 16-core configuration is designed for performing parallel computations at the CPU level. This is better suited for scenarios involving the simulation of multiple independent models (e.g., power system model, multiple controllers). Such operations must be performed simultaneously on dedicated cores [12].

Simulators from Typhoon HIL [13] provide integrated solutions for power electronics. Platforms from Typhoon HIL are optimized for testing controllers (ECU) in industries such as electric vehicles, battery management systems (BMS), and solar and wind inverters.

Simulators from this company feature ultra-low latency and a very small simulation step. The current HIL606 software ensures a simulation step (timestep) down to 25 ns and PWM input resolution (GDS) up to 3.5 ns. The Typhoon Test Hub toolkit allows automating testing processes. The software also includes tools for loss analysis, thermal analysis, and digital modeling.

The entire HIL606 platform is built on a single System-on-Chip (SoC), specifically the AMD/Xilinx ZU9EG Zynq UltraScale+ MPSoC. This choice is decisive for the entire system. The Zynq UltraScale+ architecture combines a processing system (CPU) and programmable logic (FPGA). CPU: The system has 8 computing cores. FPGA: UltraScale+ programmable logic is integrated into the ZU9EG SoC.

Unlike OPAL-RT, where the Xeon CPU and Virtex-7 FPGA are separate components connected via a bus with latency measured in microseconds, HIL606 has the CPU and FPGA on a single chip.

It has a fixed configuration: Analog Inputs (AI): 32 channels, Analog Outputs (AO): 64 channels. Digital Inputs (DI): 64 channels, Digital Outputs (DO): 64 channels. ADC/DAC resolution: 16 bit, Analog I/O range: ±10 V, ADC sampling rate: Up to 1 MSPS (1 μs step). Analog output update rate (AO): Up to 200 ns, GDS Oversampling (Digital Input): 3.5 ns [13].

National Instruments (NI) offers a different approach: a modular and flexible system based on the PXI (PCI eXtensions for Instrumentation) hardware platform and VeriStand software. The advantage of NI products lies in their openness and flexibility. The PXI platform can be configured by the user with various I/O boards and FPGAs [14].

VeriStand software for HIL testing can import models from various environments, including Simulink. It can also integrate third-party simulators; for example, Opal-RT offers its eHS solver as an add-on running on NI PXI FPGA boards. This gives users the ability to apply diverse configurations via LabVIEW, C/C++, or Python. This opens wide possibilities for integrating LLMs, which can automatically generate Python scripts for VeriStand, creating flexible, adaptive, and comprehensive validation testing cycles.

The foundation of the platform is PXIe-1095.20. Its key characteristics: Bus: PCI Express Gen 3 technology. Bandwidth: 24 GB/s throughput. CPU: 11th Gen Intel Core processors, e.g., PXIe-8842 with 6-core i5-11500HE. OS: Supports Windows and NI Linux Real-Time.

NI offers two main approaches to processing on FPGA and I/O. Approach 1: R-Series (Integrated I/O on module). This approach is represented by the PXIe-7868 module. FPGA: AMD Kintex-7 325T. Integrated I/O (per 1 board): 6 analog inputs. 18 analog outputs. 48 bidirectional digital channels (3.3V). Key architectural differences are presented in the following three tables for accurate comparison.

Table 2 – Comparison of central computing resources and memory

Parameter	OPAL-RT OP5707XG2-08	OPAL-RT OP5707XG2-16	Typhoon HIL HIL606	NI PXIe (Example Config)
CPU Model	Intel Xeon Gold	Intel Xeon Gold	ZU9EG (ARM Cortex-A53)	Intel Core i5-11500HE
CPU Cores	8 cores	16 cores	Up to 8 cores	6 cores
CPU Frequency	4.2 GHz	3.9 GHz	~1.5 GHz	Up to 4.6 GHz
System DRAM	32 GB	32 GB	16 MB per core	Up to 64 GB
Internal Storage	1 TB SSD	1 TB SSD	M.2 Slot	512 GB NVMe SSD

Source: [12-14].

Table 3 – Comparison of I/O subsystem specifications

Parameter	OPAL-RT OP5707XG2	Typhoon HIL HIL606	NI PXIe-7868 (1 module)
Analog Inputs (AI)	Up to 256	32	6
Analog Outputs (AO)	Up to 256	64	18
Digital I/O (DIO)	Up to 256	64 In / 64 Out	48 (bidirectional)
ADC Resolution	16 bit	16 bit	16 bit
AI Voltage Range	±20V	±10 V	±1V to ±10V

Source: [12-14].

Table 4 – Comparison of key real-time performance indicators

Parameter	OPAL-RT (with eHS)	Typhoon HIL HIL606	NI PXIe-7868 (1 module)
Min. Time Step	90 ns	200 ns	~1 μs
AO Update Rate	90 ns	200 ns	1 μs
DI Resolution	625 ps	3.5 ns	<10 ns
Bus Bandwidth	1-5 Gbit/s (SFP)	Integrated in SoC	24 GB/s

Source: [12-14].

The capability of AI to handle disturbances depends directly on the control system's sampling frequency. The utilization of modern HIL platforms and FPGA controllers ensures a calculation step in the range of 90–145 ns. This enables the control system to accurately process signals and adapt to load variations for converters operating at switching frequencies of up to 500 kHz – 1 MHz. With this speed, an AI agent can respond to disturbances within 1–3 switching periods, which is sufficient to prevent emergency conditions and loss of energy efficiency [15, 16].

The emergence of powerful LLMs opens new possibilities in designing and analyzing complex power circuits. Modern language models can be divided into two main categories, the choice between which is determined by the balance between performance and cost.

Models accessible via API: They usually demonstrate the highest speed and are better suited for use in other software environments.

1. OpenAI: The current model is GPT-5.2, providing high performance in code generation, text analysis, and powerful multimodal capabilities [15, 16].
2. Anthropic: Claude 3.5 Sonnet [17] offers differentiated models. The current model is Claude 4.1 Opus. It is positioned as a model with the best capabilities for complex logical reasoning. Currently, Sonnet 4.5 is considered the leading model for practical coding tasks and agent workflows.
3. Google: Gemini 3.0 Pro [18] is well-suited for analyzing large volumes of data, such as hundreds of PDF pages, long videos, or large amounts of code.

Open-Source models are available on the market. These models, although slightly inferior in general performance, can be freely downloaded, modified, and used directly on a local computer without using an API. This can be important for security-sensitive developments.

An example of this model is Meta Llama 3 [19], which has high accuracy and powerful logical capabilities. CodeLlama is a family of models specifically trained on code, making them a better choice for code generation and analysis tasks. Mixtral 8x22B is more productive compared to Llama 3 70B, has higher operating speed, and lower computational resource requirements. The current version from Meta is Llama 4, which includes the Llama 4 Scout and Llama 4 Maverick models. Also available are Mistral AI models including Mistral Large and Mistral Medium 1.1. They are created for specialized code generation tasks. The SOTA open-source model is DeepSeek-Coder-V2, trained on 6 trillion tokens, 87% of which is program code.

For tasks such as modeling the operation of switched-mode converters, AI capabilities beyond simple text generation are required. An AI capable of analyzing large volumes of data and generating responses at high speed is needed. Testing on HIL platforms generates huge volumes of files that AI must analyze and generate a response for. Here, it is necessary to choose an AI capable of analyzing as much data as possible. Gemini 3.0 Pro can use up to 2 million tokens, Claude 4.5 Sonnet up to 200k tokens, and GPT-5.2 up to 128k tokens. However, the largest available token volume is offered by the open-source model Meta Llama 4 Scout – 10 million tokens, allowing for the analysis of the largest arrays of HIL test logs in a single iteration.

Table 5 – Comparative characteristics of leading LLMs

Model	Developer	Type	Max. Tokens	Key Advantage
Claude Sonnet 4.5	Anthropic	API	Up to 200k	Code generation for practical tasks, coding.
GPT-5	OpenAI	API	Up to 200k	Versatility: Powerful agent behavior, coding, and multimodality.
Gemini 3.0 Pro	Google	API	Up to 1M	Analysis of large datasets.
Llama 4 Scout	Meta	Open-Source	Up to 10M	Data analysis: Largest available token count for analyzing large volumes of data.
DeepSeek-Coder-V2	DeepSeek-AI	Open-Source	Up to 64k	Code specialization: Trained on 87% code, best local coder.

Source: [16-19].

Table 6 – Comparative characteristics of leading LLMs (Modalities and Pricing per 1M tokens)

Model	Modality (Input)	Input Price ($/1M)	Output Price ($/1M)
GPT-5 Pro	Text, Image, Audio, Video	$15.00	$120.00
GPT-5	Text, Image, Audio, Video	$1.25	$10.00
Gemini 3.0 Pro	Text, Image, Audio, Video	$1.25	$10.00
Claude Sonnet 4.5	Text, Image	$3.00	$15.00
Llama 4 (Scout/Mav.)	Text, Image	Self-hosted	Self-hosted
Mistral Large 2	Text only (image via Pixtral)	$2.00	$6.00 - $9.00
DeepSeek-Coder-V2	Text/Code only	Self-hosted	Self-hosted

Source: Table developed by the authors, data taken from sources [16-19].

Based on the conducted analysis of available solutions and the comparison of their efficiency, a plan for modeling the QRC circuit using AI and implementing adaptive control was developed.

It is necessary to create a QRC model using MATLAB with the built-in Reinforcement Learning Toolbox. It is required to develop and programmatically integrate an adaptive DRL controller [2]. Implement DRL agent training in the created Simscape model environment, setting the task to minimize switching losses during operation with dynamically changing power switch operating modes. A key strategy is using data-driven learning: the agent is first trained on a large static dataset generated in offline simulation, and only then deployed for validation on the HIL platform. It is necessary to automate testing, for which Gemini 3.0 Pro should be used to generate operation scripts. The main task is to combine stable operation and loss minimization under dynamically changing loads.

Conclusions. It has been investigated that increasing the energy efficiency and stability of QRCs under dynamically changing loads is achieved by combining hardware and software solutions. It was determined that for the implementation of adaptive control, the optimal combination is the MATLAB/Simulink environment for training reinforcement learning (DRL) agents and HIL simulators based on FPGA (Opal-RT) for subsequent simulation and investigation of timing characteristics in the nanosecond range. The integration of modern LLMs into the development process allows for the automation of result analysis and code optimization, making the proposed comprehensive approach an effective tool for increasing the energy efficiency of power switches when working with variable loads. Future research will focus on the practical implementation and development of models and control algorithms. The development and training of a DRL agent for adaptive control of the power switch are planned.

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ПІДВИЩЕННЯ ЕНЕРГОЕФЕКТИВНОСТІ КВАЗІРЕЗОНАНСНИХ ПЕРЕТВОРЮВАЧІВ ЗА УМОВ ДИНАМІЧНИХ НАВАНТАЖЕНЬ ЗАСОБАМИ АДАПТИВНОГО КЕРУВАННЯ НА ОСНОВІ ШТУЧНОГО ІНТЕЛЕКТУ ТА МОДЕЛЮВАННЯ

У статті розглянута проблема підвищення енергоефективності сучасних систем електроживлення, де ключову роль відіграють квазірезонансні імпульсні перетворювачі (КРІП), здатні мінімізувати комутаційні втрати завдяки режимам м'якої комутації. Актуальність теми підсилюється переходом на сучасні швидкісні транзистори, що дозволяє працювати на надвисоких частотах та потребує покращеного керування. Наведено математичні залежності для розрахунку миттєвої та інтегральної потужності втрат, що дозволяє кількісно оцінити енергетичну ефективність силового ключа. На основі аналізу часових діаграм виявлено, що на п'ятому інтервалі комутації виникають незатухаючі коливання, які порушують умови перемикання при нульовому струмі. Метою дослідження є розробка комплексної методики підвищення енергоефективності КРІП шляхом впровадження адаптивного керування з використанням глибокого навчання з підкріпленням (DRL) і великих мовних моделей (LLM). У статті систематизовано та порівняно сучасні програмні середовища симуляції (MATLAB/Simulink, PLECS, OpenModelica) за критеріями точності та швидкодії. Виконано аналіз апаратних HIL платформ, порівняно їх здатність реалізувати наносекундні процеси перемикання. Особливу увагу приділено порівняльному аналізу можливостей провідних мовних моделей щодо автоматизації генерації керуючого коду та обробки великого об'єму даних результатів роботи. Запропоновано комплексне рішення: інтегрувати середовище MATLAB та великі мовні моделі для покращення стабільності та енергоефективності роботи силових ключів у реальному часі. Поставлено цілі на майбутні дослідження щодо практичної реалізації запропонованих алгоритмів на фізичних контролерах.

Ключові слова: *квазірезонансний перетворювач; комутація при нульовому струмі; адаптивне керування; напівнатурне моделювання; штучний інтелект; навчання з підкріпленням; великі мовні моделі; енергоефективність.*

Рис.: 3. Табл.: 6. Бібл.: 19.

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