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Article

An Overview of Energies Problems in Control and Robotic Systems

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Abstract: Considering the actual world economical trends, one of the most important questions is now and in the future: how to reduce power consumption of electronic systems. Since the invention of computers, the electrical energy consumption step by step increased. Now when not only computers, but electric vehicles, robots, automation, and unmanned aerial vehicles play a very important role of our life, the main problem of system designers is how to reduce energy consumption in these systems. But also the existing already working systems must be revised in order to decrease their electric power consumption. The importance of this subject (energy control) shows that a huge number of research publications and survey papers deal with it. Just focusing on the last one or two years (2021 and 2022) the search hit 221000 titles (103000 hits only in 2022). Analyzing all the research areas is almost impossible, but focusing on some important research subjects, where one of the main topic is "energy saving methods" can give an overview about the subject. The paper focuses on the area of industrial robotic systems, electric vehicles, and embedded systems.

Keywords: energy; renewable energy; robotics; drones; automation; embedded systems; system on chip

1. Introduction

Power consumption of electronic devices was always one of the main problems in embedded system design, robotics, and vehicles. In the last time in the new "everything electrically powered" era this is and will be the main problem. The field of energy production and power consumption of electrical devices – in the case of this review: automation, robotics, unmanned aerial vehicles (UAV), embedded systems, internet of things, and Autonomous vehicles (AV) – became a controversial problem in light of the events of recent years (such as pandemic, war, energy crisis, semiconductor industry crisis, etc.).

Humanity is facing the biggest challenge since the invention of steam engine or maybe earlier other technology inventions. Certainly, every crisis can lead to new technology inventions. Electrical power production probably now will focus on renewable energies such as solar, wind, and hydro-power energy production. It is very difficult to overview all the fields where robotics and process automation come to solve the increasing energy demand or to overview the robotics and embedded systems energy problems.

The energy problem in control and robotics may have many aspects. This paper does not intend to present a perfect survey about the *"Energy Problems in Control and Robotics Systems"*. If one just searches several sites then will realize that the subject is so huge, that it is almost impossible to treat all the aspects of the subject. Just to mention that searching

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"scholar.google.com" for the following search *"reduce energy consumption in robotics"* arise 17100 titles, since 2021. Another search topic was *"reduce energy consumption in embedded systems"* – this gave 16200 titles. Can conclude that in almost two years one of the major problems of the research community was how to reduce the energy consumption of all kinds of electrically powered devices.

This paper will try to give an overview about three main topics, which were considered very important by the authors. These fields where reducing energy consumption is a hot topic are as follows:

- industrial robotic systems;
- autonomous vehicles;
- embedded systems.

Since the subject treated had many reviews in the last years, the authors tried to concentrate on the literature review of the last few years. Beside introduction, the paper is organized as follows: Chapter 2 presents a background overview about the research topic of "reducing electrical power consumption" based on some reviews published since 2017. Chapter 3 treats the energy problems in industrial robotic systems, while chapter 4 gives a review of the energy problems in autonomous vehicle technology. chapter 5 presents an overview of energy consumption problems in Unmanned Aerial Vehicles. Moreover, Energy consumption problems in embedded systems and Internet of Things are presented in chapter 6 and chapter 7, respectively. Finally, some conclusions and suggestions are given to inspire the reader about the future directions can be taken in order to optimize the energy consumption in different systems.

2. Background

In the last five years there can find many reviews of the treated subject [1], [2], [3] and [4]. This chapter gives an overview of energy problems based on the mentioned reviews in the field of robotics, Autonomous vehicles, and embedded systems. In [1] the authors overview how to reduce the energy consumption in industrial robots. As the authors state mechatronic industry use robots. Energy consumption can be reduced with several methods [1]:

- Developing energy-efficient motion planning;
- Optimizing operating parameters of industrial robots;
- Optimizing industrial robot operations;
- Commercial and industrial solutions for reducing energy consumption of industrial robots.

Paryanto et al. [1] also mention that modeling and simulating the industrial process can find the weak points of the production line, where with a careful design the energy consumption can be reduced. Finally, it concludes that the use of all mentioned methods is difficult to apply because of many technical problems. But as a new possibility, the process simulation can help the early design of energy reduction. As mentioned "The simulation approach as a new trend in this field is a promising method due to its use in several manufacturing systems' development stages, from production planning to process optimization stages. Therefore, in this research, a modular model of IR for analyzing their power consumption and dynamic behavior is proposed" [1].

Energy saving methods for robotic and automatic systems were treated also in [2]. Carabin et al. [2] analyze deeply the energy saving methods in robotics and automation. Energy saving must be considered from the design stage of the robots. The above mentioned paper considers – correctly – that robots are embedded systems also. In this way, several design considerations are presented and deeply analyzed [2]. The design considerations are as follows:

- energy saving with hardware design:
    - robot type, which select the optimal solution for energy-saving using mechatronic solution;

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  - hardware replacement with newer low power components.
  - hardware addition for energy storing and recovering;
- energy saving with software methods:
  - robot trajectory optimization;
  - operation scheduling;
  - optimal control strategies.

The authors [2] analyze the above mentioned methods. One thing should be added to the methods above mentioned. The main hardware component of robots and automation systems are the micro-controllers and system on chip. These components are already capable to reduce the energy consumption of the system by entering power-save mode when it is necessary. One should mention that real-time operating systems used in the embedded systems are capable also to save energy by reducing electrical power consumption when the system allows it. Also note that the [2] is one of the most complete analyses of the energy saving methods in robotics since 2017.

In [4] because of the increasing importance of electric vehicles (EVs), the authors review the effects of the battery degradation process on energy saving in EVs. It is said that electric vehicles have low-carbon and environmentally friendly attributes. But the truth is that they move the environmental effects to the electric power plant from the place they are in traffic. Certainly, we admit that extensive research has been undertaken to decrease the changes in climatic conditions due to air pollution. Batteries are widespread in EVs as excellent energy storage devices. EV may have the disadvantage of battery long recharge time, "impact of additional strain on the grid, poor societal acceptance due to high initial costs, and a lack of adequate charging infrastructure" [4]. Fanoro et al. [4] (paper published in 2022) in their review article described battery degradation, degradation mechanisms, and types of degradation. Based on all energy reduction solutions stand the embedded systems. Embedded systems can reduce power consumption in the plant (system) since they are integrated, but also fasten the energy optimization techniques [5]. In this paper Richa et al. review the power consumption of Field Programmable Gate Arrays (FPGA) and Application Specific Integrated Circuits (ASIC). In some applications, high speed and high performance are the requirements of the embedded system then which will increase energy consumption. The system designer has to consider keeping the speed/performance versus the power consumption trade-off at a minimum. In [5] there are presented the optimization methods for the following components:

- System components and integrated circuits all kinds.
- Intellectual Property (IP) modules known as reusable fully tested circuits, used in FPGA and ASIC.
- Microprocessors, multiprocessor systems, System on chip; their power consumption heavily depends on the system clock frequency and application software.
- Customized instruction set architecture circuits are highly optimized for hardware implementation.

Embedded systems as the basis of control systems of robots, unmanned aerial vehicles, and automation systems (since their introduction) had a very important design parameter, which is to keep the power consumption as low as possible. For the embedded system components there are presented several energy optimization methods in [5]:

- The energy optimization problem in embedded system hardware can be analyzed by extensive system simulations. This possibility is given by all Computer Aided Design (CAD) tools and also by the FPGA and SOC development tools. This possibility was also analyzed in [5] and gives estimation error of power estimation between 5% to 55% or higher depending on the component types.
- Learning-based methods, which are subsets of artificial intelligent methods, provide automatic power consumption estimation resulting from experience and using data sets. This method uses neural networks for optimization. This method gives estimation accuracy between 2% to 10% depending on the component.

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- Statistical-based methods, which have common features with the simulation method. This method consists of applying test vector sequences on the circuits and the tests are running until a power estimator gives satisfactory results. Estimation errors are around 12.5% to 40% also depending on the component type.
- Measurement-based methods are a common approach for the already implemented hardware and use several built-in onboard and on-chip sensors. The estimation error is mentioned only for microprocessors and SOC – estimated to be higher than 30% for one core and higher than 4% for 16 cores [5]

Richa et al. [5] gave a detailed discussion about the power estimation methods, which were analyzed on several criteria such as: hardware and software dependency, circuit characterization based on modeling, estimation effort, estimation error, modeling effort, and modeling levels. Embedded system power consumption is divided into dynamic and static power consumption. The paper [3] also starts from this premise and presents the methods for energy saving in embedded systems. Without reducing the overall merit of the authors, we do not agree with the opinion of [3] that the family of embedded systems is included mobile phones. In our point of view, mobile phones today (2022) are much more multitasking computers and less embedded systems. By definition – from many – embedded systems execute always the same task, and can have (or not) an operating system. Since 2015, mobile phones became for the large much more a general usage computer – without enumerating a large number of applications, which are used in such complex devices.

But the authors of this paper recognize that in [3] are reviewed the methods, which contribute to the energy saving problems in embedded systems. Starting from the point of embedded systems characteristics, such as the limited size of the battery, computation speed, and limited ventilation possibilities result in the necessity to reduce energy consumption in embedded systems. However when increasing computation speed (increasing clock frequency) may result in electrical power consumption. But looking at the fact that FPGA and SOC (System on Chip) can save energy and increase the computation speed by real parallel data processing. In the meantime, one should mention that FPGAs and SOCs still are not characterized by the lowest power consumption devices. M. Sparsh [3] based on the referred literature presents the following energy reduction methods in embedded systems:

- dynamic voltage and frequency scaling and power-aware scheduling based techniques;
- low power mode management – permitted by the chip technology and operating systems;
- micro-architectural changes in memory management, sometimes adding extra components;
- using non-conventional chips such as digital signal processors (DSP), Graphic Processor Units (GPU) and FPGA. – One should add also SOC or MPSOC (multi processor system on chip);
- also we mention software methods for energy reduction in embedded systems.

The first three methods are deeply analyzed in the mentioned paper [3]. The author highlights the advantages of using FPGA (we add SOC and MPSOC) and the important role they occupy in the energy reduction methods in embedded systems.

3. Energy Consumption Problems in Industrial Robotic Systems

Due to its importance, reducing energy consumption and solving power problems in robotic systems become the most important subject in the energy research field. Many researchers tried to solve energy problems and improve the power efficiency of these robotic systems. They used various methods, some of them depend on changing the whole mechanism and others tried to improve this efficiency by using modern circuits (FPGA) and Advanced machine learning Algorithms. In [6] the energy-saving methods of industrial robots are divided as follows:

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- mechanical change of robotic system;
- after experiments change the characteristics of the existing robotic system, such as acceleration, speed, and jerk;
- creating a virtual model of the robotic system to calculate the optimal parameters;
- using energy recuperation methods;
- optimal trajectory planning using modern control methods such as model predictive control, neural networks or artificial intelligent methods, etc;
- process planning considering the energy optimal time for idle states.

Tomas et al. [6] searched for methods to decrease power consumption in industrial robotic systems. One of these methods does not need to change the existing hardware (such as robots or transporters) but to program the parameters of the system with an advanced energy optimal movement or path.

Analyzing the above-mentioned saving method Thomas et al. [6] propose two methods to find the best parameters to minimize power consumption:

- experimental method (testing parameters on the real system;
- simulates the robot operations with a virtual model.

Wei et al. [7] worked to build an optimal path for two nodes of a robotic arm by optimizing the robot's consumed energy and avoiding moving obstacles. They convert the original optimization problem into a quadratic programming problem with equality and inequality constraints, and they use neural networks AI (Artificial Intelligence) to find and solve the optimal path problem. As a result of the simulation, the increased node constraint can ensure the actual path of the generated path and improve the safety of the actual operation and minimize the power consumption.

Hovgard, et al. [8] worked on a method to reduce the power consumption of robot stations. The problem is defined as a convex mixed integer nonlinear optimization problem, and the goal is to reduce the power by using the optimal operation time and order of the robot movements. They used a simulation model of the station to find simplified power models of the robot movements. After that, they used that model to solve the optimization problem. And they tested different types of parameter settings such as reduced speed and acceleration. With the same cycle time of the station, the results display about a 12% of reduction in power consumption.

Pellegrinelli et al.[9] used Dijkstra algorithm (the principals of using the algorithm and a probabilistic map are described in Karaman and Frazzoli [10] or Parketal.[11], which identify the energy optimal path of every task and the energy consumption of overall mean of series of movements decreased by 12% for the price of 38%time extension. After this operation, they have energy optimal and collision free Path. It is important to say that this optimal path comes from a probabilistic road map, so the accuracy depends on the sampling of this road map. Finding the energy optimal path was tested in the simulation of the robot manipulator COMAU NS16-165. The main problem of power optimal planning is to calculate the consumption of every movement and find the power optimal path while it is collision-free. With the Absence of the digital model of the robotic system, the only way is to experimentally test movements and measure power consumption. The best option is when exiting a virtual model of the robotic system, In this case, we can change speed, acceleration, and complete path. This will need requirements to test if the final path is collision-free. So this method must consider time-energy difficulty. The first task of the optimization method is to find all collision-free paths, this can be done in robot software. This task complexity is very high with the increasing number of degrees of freedom. It is very important to set a criterion for path optimization. You can find Some methods to plan a path in Pellegrinelli et al. [12], Lavalle [13], Benotsmane [16].

Gadaleta et al.[15] controlled the Delmia Robotics with Python script, so we can change parameters and calculate the path and the position of the robotic system with the time axis. They determine the energy consumption of every activity with the knowledge of the path, time the movement, parameters of speed and acceleration, and a sufficiently accurate model of the robot. Figure 1 and 2 shows the simulated data obtained by Tomas et al. [6] and

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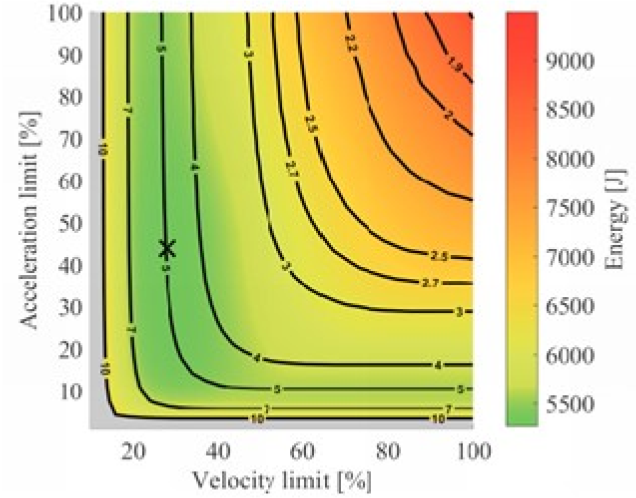

Figure 1. Energy consumption and movement time as a function of acceleration and speed [15] .

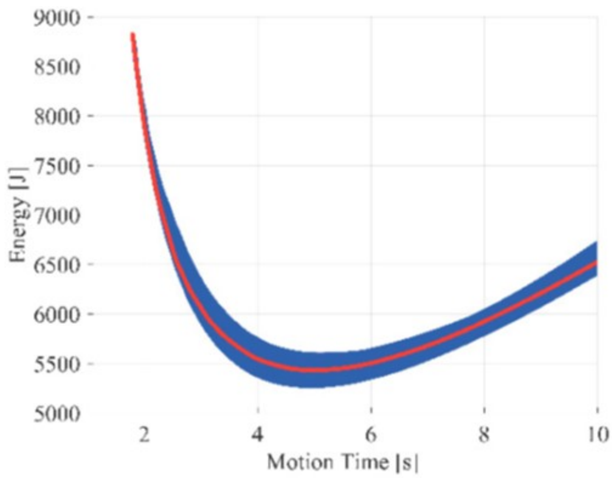

Figure 2. Energy signature (red line) compared to possible energy consumption variations when varying speed and acceleration [15].

determined the optimal parameters of speed and acceleration, which can save up to 40% of energy consumption when one takes minimal time against optimal energy consumption. Figure 1 displays various settings of speed and acceleration, which can optimize energy consumption without time losses. The optimal solution using this method can have a long setup time because of the software given by the robot manufacturers.

Calculating the optimal path of the robot may be considered the most time difficult issue and can be done by the robot software. The whole process of finding the best parameters for every production line working robot is time-consuming because of the updates of robot manufacturers' software. If there is communication between cooperating robots working on the same production line then further energy optimization results from synchronizing the robots and minimizing the dead times Benotsmane [14].

Ying, et al. [17] used an MD1200-YJ palletizing robot as a research object and tried to improve the problem of power consumption using a path optimization method for the joint driving system. They created a multi-factor dynamic model of the palletizing robot based on the Fourier series approximation method and genetic algorithm. They constructed the joint path definition and the minimum total power consumption as the optimization goal. They used the coefficients of the Fourier series as improvement variables, the movement parameters of the initial and final position, and the running time constant were taken as the constraint conditions. As a result of the simulation analysis and using the optimized Fourier series, the total energy consumption was reduced by 13.1%, and dissipation energy

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was reduced by 15.3% under the same conditions. Despite the reduced power consumption, This method has many drawbacks and can be summarized as the following:

- the process had a very high jerk value and less motion stability;
- the process had very high computational complexity;
- the convergence speed to system stability was slow;
- the configuration requirements of the computing equipment were high.

Because of these reasons, the method presented by [17] may have limited usage in practical engineering applications. One can conclude that the main problem in the industrial palletizing is power saving. Furthermore, power consumption and low flexibility are considered the main problems, which most of robots suffer from.

Deng Y. et al. [18] give a novel differential advanced algorithm to solve the instability of the initial path parameters and its bad effects on reducing energy consumption. They developed a simplified analytical way of the palletizing robot. After that, they merge the differential evolutionary algorithm with the simplified analytical model to form a method to reduce power consumption. This power-saving method improves the initial parameters of the paths collected by the bionic demonstration system to minimize operating power consumption. Due to the actual experimental results and simulation, the optimized path parameters could effectively minimize the energy consumption by 16% [18]. Pellicciari et al. [19] searched the methods to measure the power consumption in an application used in the automotive industry, which contains about 74% of the total amount of industrial robots in the industry. The largest part of industrial robotic systems cannot measure power consumption and cannot communicate with each other. The reason originates from the problem that many methods were used to measure power consumption in industrial robotics. One of these methods is measuring the whole energy consumption of the robotic system, which can be done easily but measuring every node will become very difficult. The main parameters – as mentioned before – that are needed to measure the energy consumption of the whole system are acceleration and speed. In this case, the experimental method is the only possible way to set up parameters, but this can be very difficult and not accurate. So in [19], the authors used a virtual model of the robotic system. In this way, the robot programmer can analyze to find the best parameters from a global point of view. Nowadays every robot producer has its own software program, which can simulate at least the movement of the robotic system and give the most important measurements needed to determine the optimal parameters, which will be used to minimize the energy consumption e.g. Dalmia Robotics (Dassalut Systems), KUKA.Sim (KUKA AG), and RobotStudio (ABB). A few robot simulation models can calculate energy consumption. For other robot types, one can use a script, which reads data of position from a robotic software program and send it to software such as Matlab or any other one, which can compute energy consumption from the robot model parameters. This method is called parameter analysis. Another possibility is called parameter optimization if there is a possibility to send data back to robotic software. Using Matlab, one can change speed and acceleration and calculate the optimal parameters to achieve low power consumption.

4. Energy Consumption Problems in Autonomous Vehicles

The major ambition of the automotive industry is the marketing of autonomous vehicle (AV) technology. Consequently, research in this area is swiftly expanding across the world. However, despite this high level of research efforts, literature addressing straightforward and efficient energy approaches to the development of an autonomous vehicle research platform is sparse [20]. This review chapter highlights the main problems regarding energy in automated vehicles in the scope of both standard autonomous vehicles (AV) and electrified autonomous vehicles.

Autonomous vehicles (AVs) are emerging embedded systems, and of course, energy may be considered one of the most important related issues. The biggest challenge facing AV's energy consumption is the requirements for attached sensors, control systems, computer processing units, remote data transfer protocols, and networking hardware. These

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systems are needed to perceive the surrounding real-world circumstances and responding real-time decisions [21], [22], Ȧdditionally, vehicle weight and probably higher drag may raise the energy consumption of AVs compared to human-driven vehicles [23]. These extra loads dilate the auxiliary load profile, therefore decreasing the range of an automated vehicle. Furthermore, additional electrical loads can be appended for fully autonomous vehicles due to fail-safe requirements from the sensor to vehicle control [21]. Thus, increasing energy efficiency was the subject of numerous studies for decades.

Eco-Driving is an effective technology for realizing large energy efficiency and achieving sustainable transportation [24]. A more energy-efficient drive cycle is realized for the same route by adopting a heuristic set of goals such as eliminating stops, preserving a constant speed, limiting acceleration, and smoothing the velocity profile. In this way, energy economy improvements can be achieved by 10% for modern vehicles and 30% for fully autonomous vehicles [25]. Furthermore, applying Eco-driving can result in longer battery life and slower battery degradation [23].

The formulation of maximizing energy efficiency improvement problem as an optimal control problem can be accomplished by predicting the driving circumstances along the route through Eco-driving. These predictions can be sensed by the technology of vehicle sensors, vehicle-to-vehicle (V2V), and vehicle-to-infrastructure (V2I). Many studies showed that exploiting these factors can improve power efficiency. Predictions of traffic light signal phase and timing (V2I technology) can raise the improvement to 12-14% [26]. The use of V2I (enabling traffic light prediction) can decrease power consumption in Eco-driving [27]. Other methods are proposed using information from the leading vehicle and the data from traffic lights for red light avoidance and putting constraints on vehicles in green light queues [28], and optimizing the distribution of speed and power between the motor and engine under A/C load [29]. Furthermore, the implementation of Model Predictive Control (MPC) and Dynamic Programming (DP) has been taken into consideration in a leading vehicle following scenario [30]. Vehicle velocity prediction is an essential technique for realizing improvements in the energy economy and determines the constraints of the energy optimization problem [31], [32]. Energy saving can be degraded due to inaccurate velocity prediction [33]. Self-driving vehicle possibilities have been recognized by many researchers for adapting Artificial Neural Networks (ANN) prediction models in which their outputs can improve the power economy through control strategy derivation [34], [35–42]. Other approaches have shown remarkable performance using Deep Neural Networks (DNN) [43], and the Long Short-Term Memory (LSTM) deep neural network [44].

The energy required by AVs can be supplied from different sources like batteries, Ultra Capacitors (UC), and Fuel Cells (FC). The two important criteria of energy sources are high-energy density and high-power density. High energy sources can provide long ranges while high power sources aid to maximize acceleration [45,46]. Other demanded characteristics required for the perfect energy source like fast charging, long life cycle, long service and less maintenance, and less cost [47]. Batteries are considered the most prominent energy source for a long time for electrical vehicles (EVs) and have many different technologies that still going under research and development. Some of the common battery technologies used in EVs are Li-ion, Li-polymer, Ni-Cd Na-S, Ni-MH, Zn-air, Ni-Zn, lead-acid, and graphene. Various battery kinds possess their advantages and disadvantages that should be carefully studied while choosing. Batteries represent remarkable cause for concern because of the pack size and how much weight they add to the vehicle. The battery has an impact on range and charging time as well. In general, many preferable battery technologies have been already invented, but until now they are limited and not being pursued due to their exorbitant costs [48–55].

UCs physically store charges in two electrodes separated by an ion-enriched liquid dielectric. This technology can provide significantly high-power density. Also, while no chemical reaction happened in the electrodes; the UCs life cycle is often long. However, the absence of these reactions makes them lower energy density. Additionally, their internal resistance is low, making them highly efficient, but if charged at an extremely low state; it can result in a large output current [56–58]. Fuel Cells consist of an anode, cathode, and electrolyte between them and can generate electricity by the electro-chemical reaction after applying fuel (i.e. hydrogen) to the anode. Electric Vehicles that are powered by FCs can gain many advantages like fast refueling, low or no emissions, durability, and the capacity to produce high-density current outputs [59]. On the other side, FUs technology is high cost, requires larger fuel tanks since hydrogen has less density compared to petroleum, and has lower response time compared to batteries and UCs [56]. Since hydrogen has no color, leaking hydrogen can be seriously harmful and difficult to detect. Additionally, it is highly flammable and explosive in the event of collisions. The car industry have taken steps to assure the tank's integrity in response to these issues; they have encased them with carbon fibers. There are procedures to lock the tank outlet in case of a high-speed collision, and the hydrogen handling components can be positioned outside the cabin, allowing the gas to disperse easily in case of a leak [60].

After mentioning all of the above regarding power problems, there is also an important issue related to EVs which is charging. Since the charge is stored as DC in batteries and UCs, various voltage and current configurations are available for AC or DC charging. AC supply systems require AC-DC converter circuits to obtain the charging from the grid. DC supply systems need special cabling and installation to be mounted on stations and garages [61].

EVs are regarded as high-power loads that influence the power distribution system [62–64]. Therefore, random and uncoordinated charging actions can overwork the distribution system by raising peak demands. It can also cause extreme voltage fluctuations, increasing losses, hastening the aging of transformers and cables, lowering system efficiency and economy, and raising the possibility of blackouts as a result of network overload [65–70]. Load management and network energy efficiency can be improved with the integration of smart grid functions in the field of networking, communication, and monitoring [71–76].

The time required to reach full charge is one of the most important factors, long-time charging of batteries and UCs represents the main downside issue in EVs [24]. Charging might take anywhere from a few minutes to several hours, depending on the battery pack and type of charger [77]. Uncontrolled charging (also referred to as dump charging) occurs when there is no concern about the time of power drawn from the grid. This can cause unbalancing load, instability, minimizing reliability, and reducing power quality [64,78]. Nowadays, many fast-charging technologies exist now and are being researched [77]. Wireless charging is the technology of transferring energy between primary and secondary circuits without using cabling. However, due to health and safety issues with this technique, it is not common for commercial EVs according to the standardization organizations in each country. alternatively, FCs vehicles don't need to be charged as other EVs do. They need enough hydrogen filling stations and a practical method to produce the hydrogen [79–81].

5. Energy Consumption Problems in Unmanned Aerial Vehicle

UAV (acronym of "Unmanned Aerial Vehicle") known as a drone, is an uninhabited aircraft in the field of aerial robotics; the system can be autonomous or remotely piloted [82]. The drones can carry out various missions for civil or military uses depending on their type: this is based on the characteristics and control capabilities in different environments. The performance of a drone is measured by the way it reacts to the various factors of the environment, such as aerodynamic phenomena, disturbances (winds), etc [83]. With the evolution of technology in electronics and embedded systems, the production of minimized embedded systems and sensors became possible. Therefore, the internal body of the drone became small and optimized, in this context quadrotor type presents a great example of mini drones, where its usage in the real life is increasing, especially in the last four years, with the appearance of the pandemic and corona crisis, these systems became an excellent solution for delivery purposes and fulfill logistics tasks [84], [85], [86].

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Besides the advantages of UAVs in solving many problems in different fields, a potential drawback arises with this technology regarding energy consumption where the drone is an electric device powered by embedded batteries with a limited lifetime, this has an effect on limiting the flight time of drones, therefore, most UAV applications are unable to reach their entire target. Nowadays, researchers in many literature reviews are conducting their focus on minimizing energy consumption in UAV missions to deal with this topic. First, we should identify the proper and complete model energy consumption for UAVs, this is by identifying the key factors that directly affect the energy profile of the drone [87].

Nowadays, UAVs manufacturers of professional drones are betting everything on a great autonomy. The American drone Tailwind has broken all records by flying for 4h30 minutes in the Californian sky. Other models use fuel cells, kerosene or solar energy [88]. In this paper, we mostly focus on electric type, the small entry-level models, the nano drones or mini drones which are at the bottom of the scale with flight times between 5 and 10 minutes, where this type is still far from 1 hour autonomy. Some examples of the most powerful models like the DJI Mavic 2 Pro, the Yunnec Mantis Q or the Fimi X8 SE, can expect to fly for about thirty minutes as maximum. Apart from the capacity of the battery capacity expressed in mAh, several factors are taking into account to affect the power/energy consumption of the drone so the autonomy is limited [89]:

- Impact of taking off;
- Impact of movement (hovering - horizontal movement - vertical movement);
- Impact of payload, increasing the mass of the drone affect the gravitational force, where an energy is needed to keep the drone flying by keeping the stability;
- Impact of speed, increasing the velocity of the drone is achieved by increasing the torque of the rotors which require high current.;
- Impact of wind, where the wind is a disturbance that affect the movement of the drone, therefore an opposite force should be applied to compensate it, this opposite force is generated with higher energy consumption;
- Impact of communication, where an internal communication is executing with different sensors, between the controller and sensors as GPS - Gyroscope - accelerometer - etc.

5.1. Performance energy of power source in UAV

The power source system in the drone can be characterised by different types [90], such as batteries, solar power, fuel cells, combustion engines, etc. Figure 3 shows drone power sources with different types of material.

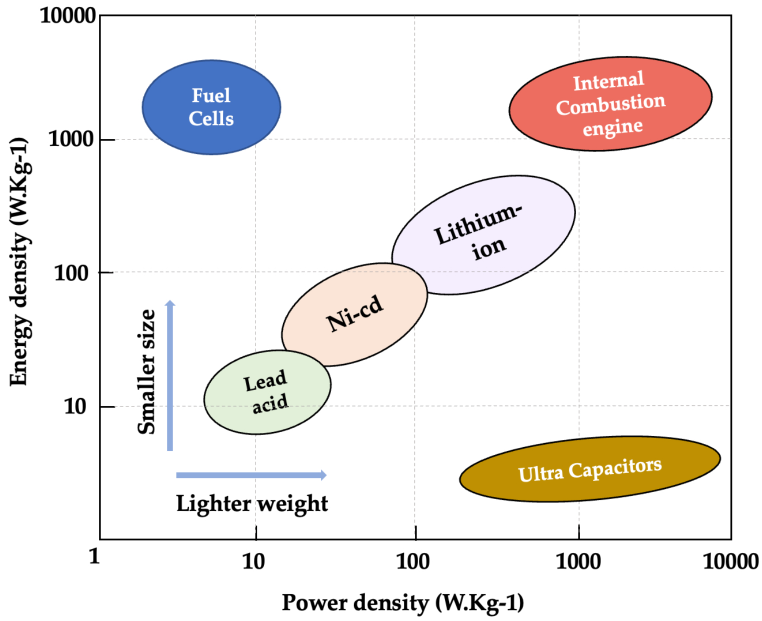

Figure 3. Drone power sources with different types of material

UAV is usually powered by a 12V battery. It is composed of different motors controlled by ESC motor controllers (electronic cards that allow to make the motors turn more or less quickly). Thanks to the propellers connected to the axes, the drone can move with 6 degrees of freedom according to the three axes [91]. Different sensors are board on the drone body:

- gyroscope measures the orientation of the drone;
- accelerometer measures the linear acceleration;
- ultrasonic measures the distance from a target.

These sensors send information to the flight controller. The telecommunication module allows receiving the orders transmitted by the by the pilot's remote control to indicate the positioning and to transmit the video signal. Figure 4 shows the drone body components, while Figure 5 shows the relation between these modules.

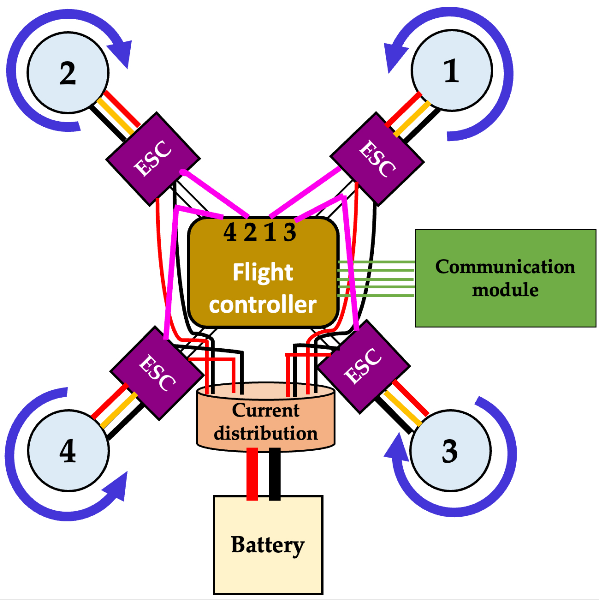

Figure 4. Drone body components

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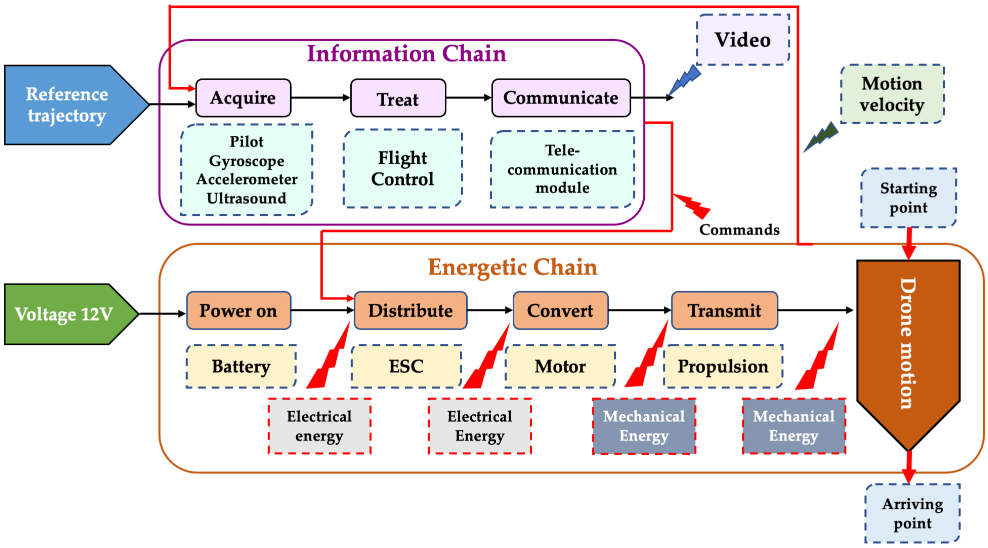

Figure 5. Relation between the drone modules

In batteries for example we find several suggestions as Lithium-ion, nickel cadmium, Lithium polymer, Lithium-air, Lithium-SOCl2. Every type depends on the usage and the drone's size. Li-SOCl2 – batteries afford two times higher energy density per kg compared to others. While Li-air batteries can achieve up to seven times higher, however, they are much more expensive than Li-Po and Li-ion. Usually Li-ion batteries are suitable for EV applications.

The efficient battery type for a specific drone can be identified by analyzing the following criteria:

- the power density affects the acceleration capabilities;
- energy density to identify the range;
- weight and volume which affect the range of the system;
- cycle life to find out how often the battery should be replaced;
- cost regarding the budget;
- safety and maintenance.

Where the power density is the value of power source, can provide at a specific instance, whereas the energy density is the value that determines how long that amount of power can be delivered.

Many literature reviews highlighted several solutions regarding the drawback of drone battery system, and how to optimize energy consumption of drone. Different solutions were proposed targeting the software and hardware level.

As software solutions, some of them were focus on trajectory planning, which presents a reference input for the drone and based on the data received from that input, the drone will execute the commands. Therefore generating an optimal trajectory from point to point can be an effective solution, almost avoiding the singularities of the system and the motions that require higher voltage for the rotors. Nowadays the optimal trajectory is generated combining AI algorithms as genetic algorithm, Ta-bu search etc. Another solution is adopted by researchers based on design an optimal control law, by generating a cost function from velocity and try to minimize it. Different strategies are taken in this field, some of them are linear [92] [93], [94], [95], as linear MPC (Model Predictive Control), LQR (Linear Quadratic Regulator), H^{∞}, some techniques are nonlinear as nonlinear MPC, Back-stepping and slave mode [96].

At the hardware level, a hybrid system implementation is recommended by using different power sources instead to have one almost keeping the light weight of the drone. As the drone market has different types of batteries, therefore the use of a good type can also solve the problem, latest researches started to include the technology of super-capacitors which presents a great solution to solve the energy storing problem.

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6. Energy Consumption Problems in Embedded Systems

Power consumption estimation of embedded systems is a very sensitive problem from the beginning of embedded system design. This process is crucial for energy optimization. Embedded design system parameter optimizations can result in design metric competition. Decreasing power consumption will outcome in performance and size reduction. The problem can be more critical when analyzing real-time embedded systems. Real-time embedded systems with single or multiple processors need task scheduling. A good task scheduler can save energy in the embedded system. The most critical performance parameters of processor scheduling for real-time embedded systems are reliability, execution time, and energy consumption. Optimizing the energy consumption of processor scheduling is considered very useful to achieve the balance in the time limit requirements, reliability, and increase power efficiency. In [97] is presented how to optimize the energy consumption of the processor under three constraints:

- partial ordering relations between task modules,
- time limit,
- reliability.

Xiong et al. [97] developed algorithms for increasing power efficiency usage in multiple processors real-time embedded systems. Based on DAG (Directed Acrylic Graph) and QPSO (Quantum Particle Swarm Optimization), the operating mode can be determined through a heuristic search algorithm for each processor. These algorithms were named Directed Acrylic Graph Quantum Particle Swarm Optimization algorithm version I and II (DAG_QPSO_I, and its improvement DAG_QPSO_ II). Using different operating modes, every embedded processor has different voltage, frequency, and power consumption. This results in different execution time, energy consumption, and reliability of the tasks, which changes with the operating modes of the processors. In a system with multiple embedded processors is critical the task scheduling, and to select the suitable operating mode of the processors. The presented algorithms optimize the task scheduling and as a result the power consumption is also optimized. Figure 6 shows a comparison between the performance of the two algorithms in terms of number of nodes and power consumption.

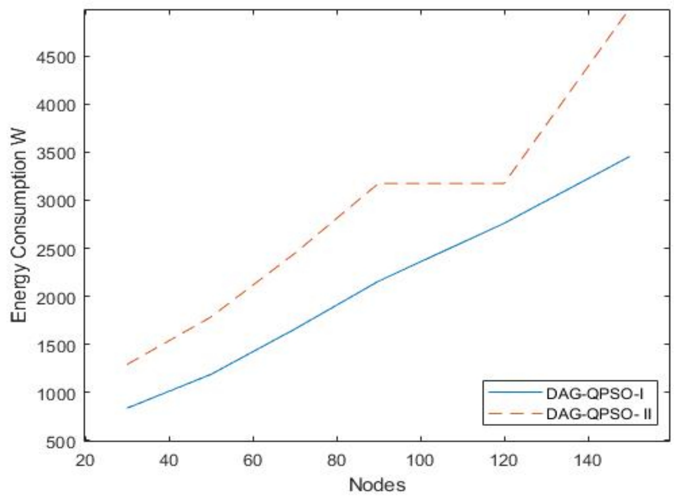

Figure 6. Comparison between DAG-QPSO-I and DAG-QPSO-II

The conflict between the energy consumption demands of current modern processors and the constrained battery capacity becomes more visible with the widespread use of real-time embedded systems. One of the best technologies for energy management has been identified the method called dynamic voltage scaling (DVS). The majority of current researches shows that the use of DVS increased processor transient fault rates, which is the result of size of logic gates (and their component transistors) gets smaller and

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smaller. Liu et al. [98] took into account the issue of allocating processing frequencies to a collection of periodic real-time functions in order to reduce total energy usage while maintaining reliability and timeliness. Depending on the meta-heuristic algorithms, Liu et al [98] achieved the best energy consumption optimization and guaranteed the embedded systems' reliability by using a modern algorithm called ADWSOA (adaptive differential whale swarm optimization) according to the optimization requirements. WSOA (Whale Swarm Optimization Algorithm) is an algorithm for function optimization which is inspired by the whales' behavior of communicating with each other via ultrasound for hunting. This algorithm is very powerful in solving multiprocessor scheduling problems [99], NP-hard problems as such as the traveling salesman problem [100], vehicle routing [101], classification problems [102], and routing problems of wireless sensor networks(WSN) [103]. After applying the ADWSOA, they saved the optimized data from the algorithm on a chain using the blockchain's storable functionality, which could affect important queries and result in a problem with the embedded system data security. Because of that, they used DPCA (differential privacy on-chain creating) algorithm to safeguard the chain's data security. The experimental results proved that the ADWSOA can minimize energy consumption in real-time embedded systems while maintaining security and reliability [98].

Because of the importance of deep learning applications in embedded systems, many researchers have directed their attention toward enhancing energy efficiency by merging neuromorphic accelerators (µBrain). Varshika et al. [104] aimed to increase the speed of SDCNNs (computations of spiking deep conventional neural networks), by designing multi-core neuromorphic hardware based on µBrain for improving energy efficiency. The capacity of the neuron cores and synaptic connections must be heterogeneous in order to reduce energy consumption (i.e., big vs. little cores). In comparison to mesh-based Network-on-Chip (NOC), the run time and power consumption will be reduced due to the manner the cores are connected to one another (using a parallel segmented bus interconnect). In [104] suggested that using SentryOS (which is a compiler and run-time scheduler) as a system software framework to link SDCNN inference applications in order to improve the throughput of the system and optimising energy consumption for existing previous design layouts. As a result of the study the improvements were:

- Energy consumption has been reduced between (37 and 98)%
- Latency has been reduced between (9 and 25)%,
- The application throughput has been increased between (20 and 36)%.

Achieving reliability and optimal energy consumption is a vital goal in designing most of the embedded systems MPSoC (multiprocessor systems on chip). Saberikia et al. [105] searched for solutions to increase the efficiency and reliability of the Real-Time MPSoC Systems by:

- Determining the safe range of speed for processors by finding the efficient points on thee of energy-reliability versus processor speed.
- Calculating appropriate speeds for the processors that run the primary task, hot and cold backups.
- Using the appropriate mapping to reduce the overlap of primary and backup tasks.

Comparing the proposed plan to the prior modern techniques, energy consumption is reduced by 11% to 42% on average while maintaining a high level of reliability of 97%.

Multicore systems need a new point of view of software engineering when using parallel computing methods. In [108] was analysed the effect of cache when using multicore systems in and embedded robot controller. From the processor-architecture level, Frequent access to register files intensively can be considered a contemporary issue of power consumption. A novel architecture is presented by [109] referred as a selective register file cache incorporated with multi-banked register file organization. This caching technique can lessen the load on the register file during read/write operations by capturing the actively reused and short-lived operands in the register file. This architecture saves about 68% over conventional embedded processors and about 51% compared to Reduced Instruction Set Computer (RISC) processor architectures. However, this saving is gained at the expense of more additional hardware usage.

7. Energy Consumption Problems in the Field of Internet of Things

K. Parmenter in [107] deals with the energy consumption of data collection of the Internet of Things (IoT). Internet of things can be looked as smart/intelligent interfaces of embedded systems. Up to Business Insights the market for the Internet of Things (IoT) products will be 1,463.19 billion USD by 2027, exhibiting a CAGR of 24.9% between now and then. IoT can collect data and interconnected to the cloud or mobiles are useful. The product range list is long when considering internet of things end products. Starting form in the field environmental data collectors to auto electronics, collected data are processed at the collection point or after transmission processed in a server, they are stored. Some times the value of data must be cheaper than the cost of obtaining and processing data. Tacking the vehicle data, or collecting someone health data with a mobile phone application the cost of IoT system and associated fees to obtain the data might be more then the information worth. IoT devices and all the interconnections needs highly efficient AC-DC power supplies or DC-DC power modules with energy harvesting solutions. Power supply devices should be efficient from the point of view of low and full load as stated in [107]. Also the power supplies have to manage the dynamically fast transient load currents and need to manage power down with very low sleep power level modes. Also IoT must be able to acquire, store and/or transmit data potentially in burst modes [107].

The Internet of Things (IoT) is a developed communication concept in which practically every device in a real-world setting is given connectivity and intelligence [110]. IoT systems need resource management strategies to guarantee service quality, avoid energy consumption, and prevent resource fragmentation. Xu et al. [110] proposed a way to manage IoT resources using a nature-inspired optimization algorithm (ABC Artificial Bee Colony) and a Markov model (MM) to resolve these constraints in order to achieve resource management strategy. In terms of execution time and energy consumption, the results showed that the new strategy was effective. Figs. 7, 8 and 9 indicate how energy consumption varies according to the number of activities, processing capacity, and nods. According to these findings, the suggested technique operates better in IoT networks than other similar strategies. Energy use is shown in Fig.7 based on the total number of tasks. The amount of energy used increases as the number of tasks increases. The suggested technique outperforms the GA (Genetic Algorithm), ACO (Ant Colony Optimization), and ABC in terms of energy consumption (Artificial Bee Colony).

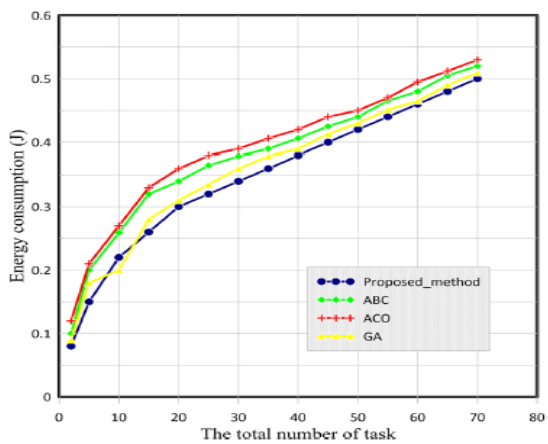

Figure 7. Comparison of energy consumption of the proposed method to ABC, ACO, and GA algorithms in terms of the number of tasks

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Fig.8 displays the relationship between energy use and computational power. All methods have drastically reduced their energy usage as processing power has grown. The suggested approach distributes tasks to IoT devices depending on the resources that can be used to process IoT devices, which utilizes the least amount of energy.

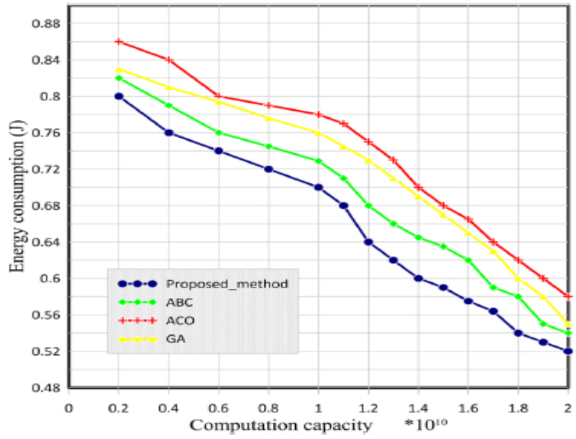

Figure 8. Comparison of energy consumption of the proposed method to ABC, ACO, and GA algorithms in terms of computational capacity

The relationship between energy use and node count is seen in Figure 9. Energy consumption rises continuously as the node count rises. It is clear that the proposed strategy performs better than alternative methods. GA is superior to the ABC and ACO approaches. ACO performs less well than other approaches, in addition.

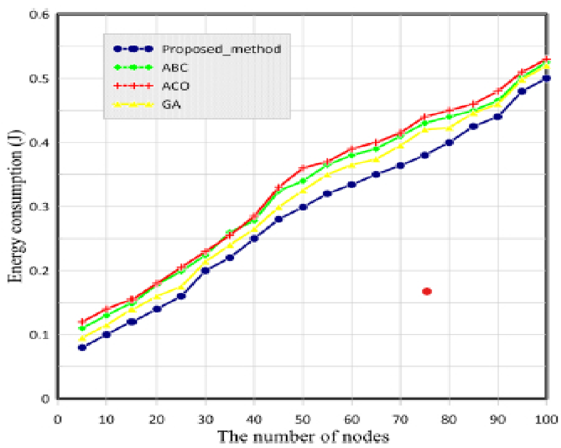

Figure 9. Comparison of energy consumption of the proposed method to ABC, ACO, and GA algorithms in terms of the number of nodes

8. Conclusions

In this paper, an overview about energy consumption of different robotic systems has been discussed. The analyses of the energy consumption regarding different systems were studied starting from the most complex systems (such as industrial robots, autonomous robots, UAV) to the basic ones (embedded systems, IoT). Most of industrial robots suffer from energy consumption, which is very hard to calculate. Due to that, all of the research focused on solving this problem with saving the reliability and reducing the execution time. The most common solution is to find the optimal path by finding the best speed and accelerating parameters. Optimal trajectory generation can be executed using AI techniques as genetic algorithm, Dijkstra algorithm, Ta-bu search, Fuzzy interpolation.

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Autonomous vehicles become very popular and fast spreading nowadays. However, energy consumption is still a hot research area up to this day. Energy problems regarding AVs can be summarized into power supply sources, the attached sensors and vision devices, control systems, networking and communication devices. Batteries are still the dominant power source, but the main drawbacks are the high cost, the limited range, and the charging time. Super-capacitors can be a solution for energy storing but they are still under research.

Eco-driving is current energy technology and can reduce power effectively. Eco driving combined with several methods like heuristic search of goals, predictive driving circumstances, velocity prediction, model predictive control, artificial neural network prediction model can upgrade the energy efficiency.

In case of UAVs, energy consumption depends on several factors related to environmental parameters such as wind and gravity related to the payload of the drone, or the type of power source which has a high effect on maintaining time flight and the communication between the pilot and the drone. These factors can be compensated using different solutions at software or hardware level. Software solutions generate an optimal path that avoids the singularities of the drone and avoid also motions that consume higher voltage for the rotors. Another solution is given by building an optimal control law that optimizes a cost function related to the velocity. At the hardware level, a hybrid system implementation is recommended by using different power sources instead to have one almost keeping the light weight of the drone. The issue can also be resolved by using a good battery, or as said for autonomous vehicle systems super-capacitors can solve the energy storing problem.

Energy optimisation problem in embedded systems will be always a problem for real-time computing with or without operating systems. The problem leads to software and hardware solutions also. Designing embedded systems is always an optimisation problem between the design parameters, such as computation speed versus power dissipation. Achieving the reliability and the optimal energy consumption is a vital goal in designing most of the MPSoC. Furthermore, an analyses is necessary for a given application if is really need to MPSoC (such as mobiles), instead to optimise the application using one processor and consuming less energy.

Internet of Things is still suffering of several obstacles as information/price ration. A good resource management strategy in data collection, store and transmission should be the solution for energy. The needed information should be available at the right time in the right place with the low cost of electric power. The resource management strategies are used to guarantee service quality, avoid energy consumption, and prevent resource fragmentation.

Finally one can conclude that can not propose a universal solution for solving the energy problems in automation and robotic systems. The solution always depends on the cost function of the problem in hand.

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Abbreviations

The following abbreviations are used in this manuscript:

MDPI	Multidisciplinary Digital Publishing Institute
DOAJ	Directory of open access journals
LD	Linear dichroism
DAG_QPSO	Directed Acrylic Graph Quantum Particle Swarm Optimization Algorithm
ADWOA	adaptive differential whale swarm optimization
ABC	Artificial Bee Colony
ACO	Ant colony Optimization
DVS	Dynamic Voltage Scaling
ESC	Electronic speed controllers
WSN	Wireless Sensor Networks
DPCA	Differential Privacy On-chain Creating)
SOC	System on Chip
NOC	Network-on-Chip
SDCNN	Spiking Deep Conventional Neural Networks
MPSoC	Multi-processor Systems On Chip
UAV	Unmanned Aerial Vehicle
GPS	Global Positioning System
MPC	Model Predictive Control
LQR	Linear Quadratic Regulator
AV	Autonomous Vehicle
EV	Electric Vehicle
DP	Dynamic Programming
ANN	Artificial Neural Networks
DNN	Deep Neural Networks
FPGA	Field Programmable Gate Arrays
ASIC	Application Specific Integrated Circuits
MPSoC	Multiprocessor System on Chip
IP	Intellectual Property
UC	Ultra Capacitors
FC	Fuel Cells
AC	Alternating Current
DC	Direct Current
GPS	Global Positioning System
SDCNN	Spiking Deep Conventional Neural Networks
CAD	Computer Aided Design
DSP	Digital Signal Processor
GPU	Graphics Processing Unit
AI	Artificial Intelligence
V2V	Vehicle to Vehicle
V2I	Vehicle to Infrastructure
LSTM	Long Short-Term Memory
RISC	Reduced Instruction Set Computer
GA	Genetic Algorithm

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