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Evolutionary Implementation of Wireless Power Mobile Edge Cloud on Low Power Robotics

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Abstract:
The advancements in robotics have caused many innovative applications to appear on the surface. These modern applications are becoming more and more resource hungry and hence the traditional conventional robotic systems in which the mechanical system carries all resources onboard are proving to be ineffective. This has led to an increase in the research of Cloud-Robotics, where Robots and other wireless mechanical systems will have their sensors and actuators intact but the computational capabilities could be utilized from a remote database server commonly known as a cloud. This research includes robotic devices offloading a part or whole of their extensive computational tasks using Binary offloading scheme to a remote cloud for processing. The reliability of the proposed model is measured by overall energy performance of the robotics network. Extensive simulation to validate the proposed solution has been conducted. Results demonstrate that computational energy efficiency of robots connected to LCCP is increased as compared to those performing their task locally. This reflects the fundamental trade-off between local computation and offloading.

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I. INTRODUCTION

The Cloud network and its vast set of Internet-accessible resources has the potential to bring major advantages to robots and automation systems. The beginning of the artificial intelligence revolution, as we see, has brought many new challenges in the field of robotics. Most of these challenges are about why, with what and how can the existing knowledge be used to meet the growing demands. All robots and robot-like devices were historically self-sufficient and independent of design. This asserted that if electric power is being received all the resources of a certain robot are available and ready to be used onboard without any external aid. This method has long worked in conventional industrial applications but the onboard resources (processor, memory, storage, etc.) are not enough to handle new challenges efficiently. Employing external tools is becoming more and more recognized when it comes to mobile and desktop computing. A number of options are available, from dedicated local network servers to public cloud services. Within cloud-related robotics research, different goals can be described in light of cloud computing paradigms. Scenarios in which physical robots embody low

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onboard infrastructures are controlled by high-level controls that are manifested in complex cloud services [1].

Cloud computing can be employed to increase efficiency of onboard resources, to allow user equipment to offload computation and storage to distant centralized clouds facilities, connecting through the Internet. While this strategy allows to save battery consumption and helps achieve a variety of tasks and applications, it also produces an increase in the latency experienced by the user and hence an increase in Quality of Experience (QoE). Offloading improves the computational performance of wireless robotic devices and reduces the consumption of energy. While devices can offload tasks into the cloud, Mobile edge computing (MEC) offers a wide range of services [2]. Offloading can be *Partial* and *Binary*. In partial offloading a part of computational tasks is offloaded to the cloud and local processing is also involved. In binary offloading, however, tasks are either computed locally or are offloaded to the cloud for processing, and never both.

As mentioned earlier, the limited service life and computing power of the device cannot keep pace with the growing number of new applications that require stable and powerful computing capabilities, such as autonomous driving vehicles (AGVs) and augmented reality [1]. It is hence important to address these two important performance constraints for research and development of modern cloud robotics technologies. The integration of wireless power transmitters and mobile technology in the cloud creates a new paradigm called *Mobile Edge Computing (MEC) wireless power supply* that can solve the problems of limited life and computational power of devices and hence increases the energy efficiency.

A. Related Work

In orthodox industrial approach, all processing capabilities and resources are present on the device but the modern cloud-based robots put only the responsibility of sensing and actuating on the physical systems and are referred as Puppet robots as their 'brain' is being controlled from a distance. Digital house aids such as Amazon's Alexa are antecedent to the cloud-based robotics era. Such systems do not carry motion capabilities at the moment but one can easily imagine mechanical systems combined with digital cloud robotics is the future [1]. The *RoboEarth* project that came out in 2009 put forth the idea of a World Wide Web for robots which is a huge network and database server where robots could share information and learn about their actions and environment from each other [3]. The 'brain' is raised in the mother system in the remote brain robotics method. These robots directly benefit from the mother systems' evolution, ensuring that when the mother system upgrades to a more powerful computer, remote brained robots have their software updated as well. [4]. "Networked robotics" subfield was initiated when a web-based interface for robots and other wireless devices was developed by researchers in the mid to late 1990s [5], [6]. The binary offloading specifies that the task is to be executed either locally on the wireless device or remotely on the cloud server. Some research has been done on this offloading technique like the author in [2] proposed a one-D search Algorithm to reduce response time, considering the state of the queue of applications and existing processing capabilities. Offloading of computational data has recently drawn attention of scientific research to increased productivity and reduced power consumption of mobile devices. The challenge is to decide what to offload and when to offload, with minimal cost of programming in the overall MEC environment. [7] The theory of prioritization is used for modeling mobile nodes of vehicle coastlines, which in [8]. The common strategy of optimizing planning with the aim of improving the quality of experience (QoE).With a average performance delay, the consumption of energy can be considerably reduced. In [9], the UE as a whole is grouped into two categories, based on the volumes of data they have to offloading. The UE of the first

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group has access to the MEC server, while the UE of the second group has access to the MEC server, while the first group only has the option to perform tasks locally. the optimal transmission power determined by depending on the distribution of communication and computing resources. In [10], the author focused on reducing the backhaul network's congested performance by calculating the common boundaries of wireless networks. However, in [11] the author formulated the problem of minimizing the energy consumption taking into account the applied buffer. An online algorithm based on Lyapunov optimization was proposed to determine the ideal CPU frequency, transfer and distribution of bandwidth resources. In [12] the problem of resource block planning is formulated in a narrow range of IoT. The heuristic algorithm takes into account both power management and the choice of relays [13].

B. Contribution

In this research work our goal is to formulate mathematical modeling to increase energy efficiency of wireless robotic devices using mobile edge cloud with integration of wireless power transmitter and using Binary offloading scheme. Evaluation of our proposed model is done by MATLAB simulation.

In this work, the concept of wireless power mobile edge cloud (WPMEC) is considered. WPMEC is located at the access point (AP) as explained in [14], where the Local Central Cloud Point (LCCP) can be a base station, a Wi-Fi router etc. The WPMEC is used for energy transfer to devices with limited power and at the same time to receive computational tasks from the devices. This work addresses *Binary offloading scheme.* The terms users, user devices, wireless devices and robotic devices are interchangeably used to address the limited power devices. The *efficiency of computational energy* is used as the performance metric.

The main contributions in this work are as follow: In order to maximize the efficiency of computational energy of our network, our system model is described as a *joint optimum allocation of transmitting power, local computing chip frequency and the transfer time using binary offloading scheme between mobile devices and WPMEC using Genetic Algorithm.* Comprehensive model examines the underlying trade-off between data size, offloading and local computation.

II. SYSTEM MODEL

In this work we consider the concept of wireless power mobile edge cloud as explained in [14], having 'n' number of robotic devices distributed uniformly in a specific area. These devices are connected to one Local Central Cloud Point (LCCP) which is the integration of wireless power transmitter and mobile edge cloud to overcome the limitation of finite battery life and limited computational capabilities of robots for advanced applications.

Each device harvests $E_{harvested}$ energy transmitted by the wireless power transmitter in the cloud using radio frequency signals. Harvested energy is utilized to perform local computations or to offload the task using *Binary offloading scheme* to mobile edge cloud located at the LCCP. Mobile Edge Cloud and Wireless Power Transmitter operate at the same frequency and in order to avoid their mutual interference, Time division multiplexing technique is applied to separate the energy signal from the information signal. In order to implement Time division multiplexing, entire time frame T_{total} is divided into two parts: Harvested time t_h and Offloading time of devices t_n as shown in figure.

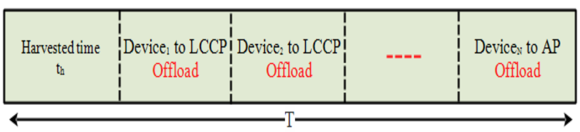

Fig. 1.1 Time division multiplexing

$$T_n = T_{Total} - T_h (1.1)$$

In time t_h devices harvest energy from the wireless power transmitter while in t_n, devices offload their extensive task having Mn bits to mobile edge cloud for further processing.

Let M_n be the number of bits produced by 'n' devices that need their computation done either locally or at the edge cloud. In order to compute the M_n number of bits locally, $f_n e$ $(0; f_n^{max})$ are the resources allocated to the nth device, whereas energy consumed to compute the number of bits locally is represented by $E_{Locally}$ and bits by $Bits_{Locally}$ respectively.

$$E_{Locally} = e_n f_n^3 t_n \quad (1.2)$$

$$Bits_{Locally} = \frac{T_{Total} f_n}{C_n} \quad (1.3)$$

Here e_n and C_n represent the computing efficiency of the device processor and number of cycles to compute one bit respectively. Furthermore, if the energy consumed to compute the bits locally is greater than the energy consumed to offload the task to the mobile edge cloud, then it is better to offload the task. Energy Consumed to offload the task to mobile edge cloud is represented by $E_{offload}$, whereas the Number of bits computed at the Edge (cloud) is represented by $Bits_{Edge}$ respectively.

$$E_{Edge} = p_r t_n + p_n t_n \quad (1.4)$$

$$Bits_{Edge} = B \log 2\left(1 + \frac{p_n g_n}{\vartheta^2}\right) t_n \quad (1.5)$$

In Equation 1.4 p_r and p_n represent the transmission power and static circuit power of the robot device respectively, whereas the channel gain between robot device and LCCP is represented by g_n. ϑ represents noise during transmission.

A. *Problem Formulation*

In the case of Binary computation, task as a whole is computed either at MEC or locally at devices, so we need a decision variable y_n that decides if the task is being computed locally or at MEC. Mathematically this Problem model is as follow:

$$\underset{t_h, y_n, t_n, f_n, p_n}{Max} \sum_k w_n \left(\frac{y_n Bits_{Edge} + (1-y_n) Bits_{Local}}{(1-y_n) E_{Local} + y_n E_{Edge}} \right)$$

(1.6a)

$$C_1 : t_h + \sum y_n t_n \le T_{Total} \quad (1.6b)$$

$$C_2 : y_n Bits_{Edge} t_n + (1-y_n) Bits_{Local} \ge M_n, \forall_n \quad (1.6c)$$

$$C_3 : (1-y_n) E_{Local} + y_n E_{Edge} \le E_{harvested}, \forall_n \quad (1.6d)$$

$$C_4 : 0 \le f_n \le f_n^{max}, \forall n \quad (1.6e)$$

$$C_5 : t_n \ge 0, \forall n \quad (1.6f)$$

$$C_6 : y_n \in \{0,1\} \quad (1.6g)$$

In Above Equations, w_n is a weighting factor used to prioritize the user based on the QoS requirements of devices. $y_n \epsilon \{0, 1\}$ is binary variable that decides either the task is being executed locally or at Edge. If $y_n=0$, it means that the computational task is executed locally on the devices otherwise computation takes place at the edge.

Above mentioned is a resource allocation problem that optimizes the offloading time both at the Access point for energy harvesting and at wireless robotic devices for offloading power and local chip computation frequency. The decision variable y_n is there to maximize computational efficiency among all devices connected to LCCP.

Table 2.1: Simulation Parameters

Parameter Name	Symbols	Values
Bandwidth	B	20kHz
Users devices	N	2; 5
Time block	T	1 sec
Chip Computing Efficiency	e_n	10 24
Maximum Computation Capacity	f_n^{max}	10^9 cycles/sec.
Harvested Energy	E_n	2 Joules

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Cycle per bit	C_n	10^3
Static Circuit Power	p_r	50mW

C1 states that all the work should be completed within time frame as represented in Figure. C2 states that the number of bits computed either at LCCP or locally at the device should be greater than minimum number of data bits for computing either at LCCP or locally and are represented by M_n. C3 states that the total amount of energy consumed should be less than or equal to the amount of harvested energy form wireless power transmitter located at LCCP. C4 defines the maximum amount of CPU frequency of robot devices.

III. RESULTS AND DISCUSSION

Simulation results were carried using Genetic Algorithm over MATLAB. Parameters used in this

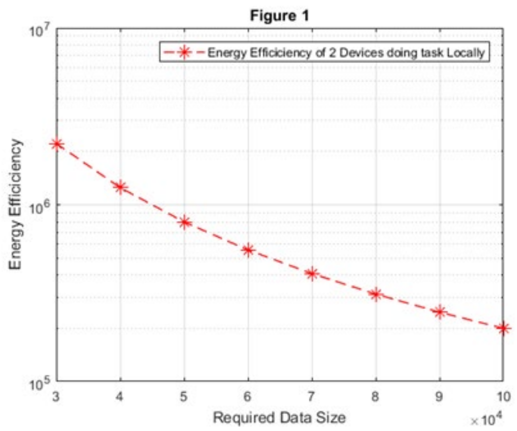

Fig. 2.1: Energy Efficiency versus Data Size Requirement using Local Computation

simulation as shown in Table 2.1 are taken from [14] whereas the channel between the devices and LCCP is considered to be static over the entire time duration T_{Total}.

Fig. 2.1 represents the comparative analysis of energy efficiency and data size requirement using local computational scheme. As the requirement for data size increases energy efficiency of the system decreases. This is due to fundamental relationship between data size requirement and energy consumption. Larger data requires huge amount of energy in order to compute it so therefore energy efficiency of the system decreases. Whereas in 5th Generation communication system, with the invention of AVG these devices are unable to meet the requirement of users.

In order to overcome the above limitation of the system, concept of mobile edge cloud using binary offloading scheme is introduced which allows these devices to compute their task either locally or completely offload their extensive task to mobile edge cloud located at the LCCP. Fig. 2.2 demonstrates the comparative analysis of local computation and binary offloading scheme using energy efficiency as the performance matrix. Results reflect that for small data size performance of local computation and binary offloading scheme is same whereas binary computational scheme outperforms the local computational scheme as the requirement for the data size increases. This is due to the fact that for small data size, energy consumed to do the task locally is smaller than the energy consumed in transmitting the task to LCCP. In this case devices prefer to compute the task locally. On the other hand as the data size requirement increases, energy consumed in computing the task locally becomes

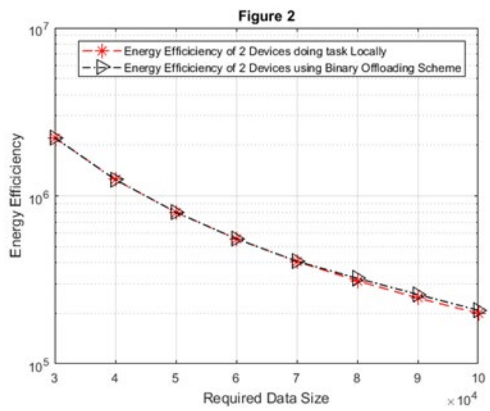

Fig. 2.2: Comparison of Local Computation and Binary offloading using 2 devices in Network

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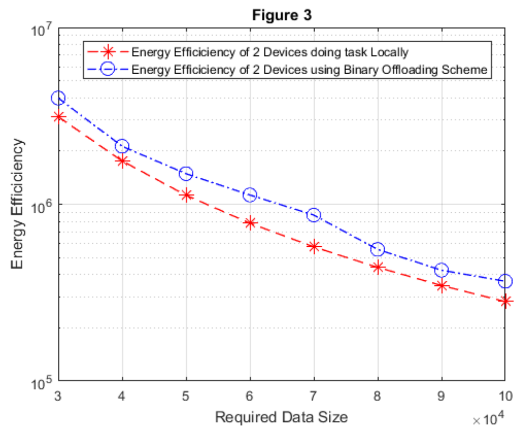

Fig. 2.3: Comparison of Local Computation and Binary offloading using 5 devices in Network

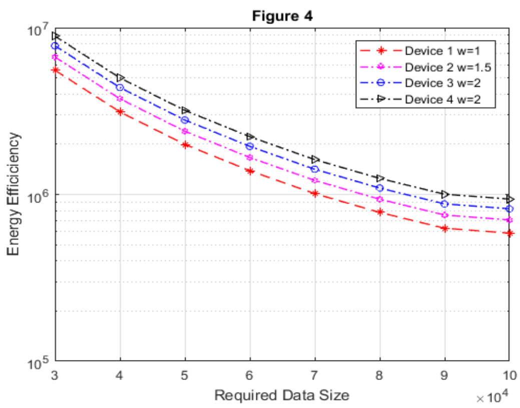

Figure 2.4: Computational Efficiency for each user using Binary offloading using 4 devices in Network

larger as compared to transmission energy. In that scenario devices prefer to offload the task for further computations. This fundamental trade-off can clearly be analyzed as the number of devices in the network increases. As the number of devices in the network increases, overhead to compute the specific task decreases.

As represented in Fig. 2.3, comparison of binary offloading scheme and local computation is carried out using 5 devices in a network. Above mentioned trade-off can clearly be seen as the number of devices increase. As priority rises, the computing energy efficiency of the consumer unit improves. In this scenario, the weight variables are used as a guide.

Fig. 2.4 displays the energy efficiencies in each system and the findings demonstrate that the high priority devices (high weight factor) are strongly measured in terms of energy efficiency compared with the low priorities devices. In an emergency situation, where the lives of each consumer are more important than overall energy efficiency, this enormous model behavior can be used.

IV. CONCLUSION

In this research an energy efficient maximization problem is presented using the wireless power mobile edge cloud by optimal allocation of resources amongst user devices The proposed model is validated through extensive simulations The proposed solution outperforms other schemes, like local computation schemes in terms of energy efficiency for different data sizes and different priorities of devices The results with different priorities have endorsed the importance of WPMEC system in emergency scenarios.

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REFERENCES

1. A. Robot, “Cloud, Fog, and Mist Computing,” pp. 41–45, 2020.
2. H. Liu, F. Eldarrat, H. Alqahtani, A. Reznik, X. De Foy, and Y. Zhang, “Mobile edge cloud system: Architectures, challenges, and approaches,” IEEE Syst. J., vol. 12, no. 3, pp. 2495–2508, 2018, doi: 10.1109/JSYST.2017.2654119.
3. B. Kehoe, S. Patil, P. Abbeel, and K. Goldberg, “A Survey of Research on Cloud Robotics and Automation,” IEEE Trans. Autom. Sci. Eng., vol. 12, no. 2, pp. 398–409, 2015, doi:

10.1109/TASE.2014.2376492.
4. M. Inaba, S. Kagami, K. Sakaki, F. Kanehiro, and H. Inoue, “Vision-based multisensor integration in remote-brained robots,” IEEE Int. Conf. Multisens. Fusion Integr. Intell. Syst., pp. 747–754, 1994, doi: 10.1109/mfi.1994.398380.
5. D. Song, K. Goldberg, and N. Y. Chong, “Networked Telerobots,” Springer Handb. Robot., pp. 759–771, 2008, doi: 10.1007/978-3-540-30301-5_33.
6. V. Kumar, D. Rus, and G. S. Sukhatme, “Networked Robots,” Springer Handb. Robot., pp. 943–958, 2008, doi: 10.1007/978-3-540-30301-5_42.
7. H. El-Sayed et al., “Edge of Things: The Big Picture on the Integration of Edge, IoT and the Cloud in a Distributed Computing Environment,” IEEE Access, vol. 6, pp. 1706–1717, 2017, doi: 10.1109/ACCESS.2017.2780087.
8. Y. Wang, I. R. Chen, and D. C. Wang, “A Survey of Mobile Cloud Computing Applications: Perspectives and Challenges,” Wirel. Pers. Commun., vol. 80, no. 4, pp. 1607–1623, 2015, doi: 10.1007/s11277-014-2102-7.
9. S. Patole, “A Survey of Mobile Cloud Computing,” Int. J. Res. Appl. Sci. Eng. Technol., vol. 7, no. 6, pp. 2438–2441, 2019, doi: 10.22214/ijraset.2019.6411.
10. S. Bi and Y. J. Zhang, “Computation Rate Maximization for Wireless Powered Mobile-Edge Computing with Binary Computation Offloading,” IEEE Trans. Wirel. Commun., vol. 17, no. 6, pp. 4177–4190, 2018, doi: 10.1109/TWC.2018.2821664.
11. S. Abolfazli, Z. Sanaei, E. Ahmed, A. Gani, and R. Buyya, “Cloud-based augmentation for mobile devices: Motivation, taxonomies, and open challenges,” IEEE Commun. Surv. Tutorials, vol. 16, no. 1, pp. 337–368, 2014, doi: 10.1109/SURV.2013.070813.00285.
12. X. Masip-Bruin and E. Marín-Tordera, “IntroductIon: the scenArIo,” no. October, pp. 120–128, 2016.
13. C. F. Liu, M. Bennis, and H. V. Poor, “Latency and Reliability-Aware Task Offloading and Resource Allocation for Mobile Edge Computing,” 2017 IEEE Globecom Work. GC Wkshps 2017 - Proc., vol. 2018-Janua, pp. 1–7, 2018, doi: 10.1109/GLOCOMW.2017.8269175.
14. A. Mahmood, A. Ahmed, M. Naeem, and Y. Hong, “Partial Offloading in Energy Harvested Mobile Edge Computing: A Direct Search Approach,” IEEE Access, vol. 8, pp. 1–1, 2020, doi: 10.1109/access.2020.2974809.