Aiming in Harsh Environments: A New Framework for Flexible and Adaptive Resource Management

Jiaqi Zou, Rui Liu, Chenwei Wang, Yuanhao Cui, Zixuan Zou, Songlin Sun, and Koichi Adachi

Abstract

The harsh environment imposes a unique set of challenges on networking strategies. In such circumstances, the environmental impact on network resources and long-time unattended maintenance has not been well investigated yet. To address these challenges, we propose a flexible and adaptive resource management framework that incorporates environment awareness functionality. In particular, we propose a new network architecture and introduce the new functionalities against the traditional network components. The novelties of the proposed architecture include a deep-learning-based environment resource prediction module and a self-organized service management module. Specifically, the available network resource under various environmental conditions is predicted by using the prediction module. Then, based on the prediction, an environment-oriented resource allocation method is developed to optimize the system utility. To demonstrate the effectiveness and efficiency of the proposed new functionalities, we examine the method via an experiment in a case study. Finally, we introduce several promising directions of resource management in harsh environments that can be extended from this article.

Introduction

Harsh environments for humans are considered as environments with extreme conditions, which are difficult or impossible for humans to survive. This description can also be extended to electronic communication devices, which in the harsh environment would experience significant degradation of network performance. As a result, even meeting the basic communication demands without special designs might be questionable. The harsh environment is usually unattended and dominated by multiple severe environmental factors, as well as the network itself. For example, in iron and steel manufacturing, the network is expected to tolerate extreme temperatures, vibration, high pressure, moisture, noxious gases, and so on; in an extreme natural environment, the network should take into account appalling weather such as extreme drought and heavy rain, and mechanical damage.

Although specially designed electronics that are made with high temperature resistance and non-corrosion materials could survive under extreme conditions [1], the resource management strategies in the harsh environment are much more complicated. In a future wireless network, resource management is recognized to play an essential role due to the highly demanded but limited network resources [2]. Recent development in [3] provided an adaptive network resource allocation algorithm in high-mobility communication systems. Framework designs based on software defined networking also enable scalable resource management, such as the work on space-air-ground integrated communications [4]. While these works successfully addressed the issues in a few scenarios, they still lack flexibility under changeable environments. In particular, resource management under extreme physical conditions has not been fully investigated. Also, in the harsh environment, the traditional resource management systems would encounter many new challenges, because dynamic harsh conditions could significantly affect network performance as well as the incapability of autonomously recovering reliable communication services under long-time unattended conditions.

When network resource management meets the harsh environment, there are two main challenges in general.

Long-Term Reliable, Autonomous Service Management with Quick Responses under the Unattended Environment: In-person maintenance is usually expensive or even impracticable for a network in a harsh environment. Thus, self-healing and self-maintenance capabilities are expected to be integrated so that the services and resources can be formed autonomously and managed to guarantee reliability and stability. For instance, the traditional network architectures (e.g., ad hoc [5]) provide flexible topology, but they lack reliability in unattended and extreme environments. When the main link fails, the ongoing transmission would be re-routed to sub-optimal backup links, which would temporarily depress the network performance. In the harsh environment, the network actually requires flexible and adaptive configuration of network resources. Moreover,
the scalability of the service management is also a key to building fast and durable solutions.

**Consideration of the Uncertainty Impact on Network Resources Caused by Complicated Environmental Factors:** Compared to normal environments where the environmental limitations have certain distribution, such as path loss and rain attenuation, the status of network resources in the harsh environment is affected and dominated by multiple environmental factors. These factors are commonly coupled and environment-dependent, so mathematical modeling is intricate. Moreover, harsh conditions often seriously suppress the network performance. Thus, the environmental impact needs to be specially considered when designing a network resource management framework.

Recognizing the challenges above, in this article, we propose a flexible and adaptive resource management framework that consists of a new resource management architecture and an environment-oriented resource allocation method. Specifically, to achieve autonomous service management, the proposed architecture realizes self-organization and self-maintenance of the services; to combat complicated environmental factors, a deep-learning-based model to predict the environmental impact on available network resources is integrated into the proposed resource management architecture, and the prediction of available network resources is taken into account in the proposed resource allocation method.

The remainder of this article is organized as follows. In the next section, we propose an environment-aware self-maintenance resource management architecture, and introduce its reliability and scalability as well as the environment perception module. Following that, we formulate an optimization problem considering resource allocation under harsh conditions. To resolve it, we first design a deep-learning-based method for available resource prediction and then develop a game-theory-based method for resource allocation. To illustrate the effectiveness of the proposed architecture, we provide a case study. Finally, we conclude this article with potential future research directions.

**RESOURCE MANAGEMENT: FROM THE TRADITIONAL TO THE NEW ARCHITECTURE**

The resource allocation in the wireless network is implemented in the resource management architecture, which has been widely investigated in literature. Although each architecture has its own attributes, a structure of three planes — application, resource, and physical planes — is usually formed, as shown in Fig. 1a. In the following, we briefly introduce the function of each plane.

The **physical plane** aggregates and controls the physical devices distributed over the space. For collaborative sensing of environment conditions and collecting real-time information, a vast number of distributed sensors should be deployed.

The **resource plane** processes the information sent from the physical plane and allocates network resources based on the carefully designed criteria of interest. The **application plane** supports a variety of services, such as intelligent monitoring, remote control, and cloud computing. The services can be task-specific applications and public platform services.

The existing architectures (e.g., [6]) decouple
the service management logic in the application plane and the control logic in the resource plane. Such hierarchical architectures are widely adopted and enable the network management to operate from a global view of a unified resource plane [7]. Similar architectural paradigms are also considered by forward-looking research in 6G networks with abundant emerging applications [8]. However, these architectures of network resource management are usually statically deployed, and hence not capable of perceiving environment and responding to dynamic harsh conditions. Also, autonomously maintaining reliable services under long-time unattended conditions appears very difficult. Thus, designing a new architecture in the presence of hard conditions is desired.

**The Proposed New Architecture**

We propose a new environment-aware and self-maintenance architecture for resource management, as illustrated in Fig. 1b. There are two main novelties in the new architecture: the prediction module in the resource plane, which is for environment sensing based on a pre-trained data-driven model; and the service management in the application plane, which is autonomous, self-maintained, and scalable to support the adaptation between the service requirements and the available resource amount. In this section, we introduce the function flow of the new architecture in each plane in detail.

First, in the physical plane, the harsh environment is an ideal use case for more capable sensors and edge computing. Different from the sensors for the normal environment, the sensors designed for the harsh environment have larger storage capacity to prepare for communication-link failure. Moreover, the edge computing server (ES) can reduce the communication delay and the bandwidth usage due to local processing. The devices can also communicate with each other with the help of device-to-device (D2D) links, thus providing emergency communications in case of natural disasters; for example, an ad hoc network can be established D2D. To boost the reliability, the devices are distributively deployed to attenuate the effect of individual failure.\(^1\) As a result, the physical plane collects the device information and the environment condition, which are then fed to the resource plane for efficiently making a more accurate decision for controlling network resources.

Second, in the resource plane, the proposed environment-resource prediction module interacts with the physical plane and the resource pool to ensure the compliance of the propagated resource schedule request. Specifically, it receives the environment information as the input and responds to the resource pool with the resource schedule request. The resource pool acts with the physical plane and the resource management logic to schedule the service on the resource pool. The available resources, such as bandwidth and power budget, are aggregated and shared by multiple services. To learn the underlying patterns behind the environment features and the output system metrics, we leverage deep learning to monitor, predict, and adapt to the resource status. Then the available network resources predicted by the prediction model are aggregated in the resource pool for resource scheduling. Note that compared to traditional resource scheduling, two functionalities are highlighted in the new scheduling module: the resources are authenticated and authorized for each service, and the resource prediction module, and then the resource control sub-module takes an action of power control, load control, radio resource control, and so on. Meanwhile, the resource scheduling also takes the environment constraints predicted by the environment-resource prediction module.

Finally, in the application plane, the self-organization and self-maintenance of services are realized. To achieve this goal, we design the service management module, which consists of the description and adaptation sub-modules, as shown in Fig. 1b. The service-description one describes the resource requirements from the services, and then the service-adaptation one makes an adaptive orchestration to generate several service groups (SGs) by grouping the services with similar functions (but their required types of network resources can be different). Due to this graph-based structure, whenever some (but not all) services are down due to the resource limitation, other services in the same SG would immediately back up. When the report from the resource plane changes, the SG organization can also be updated and optimized according to the dynamic resource states. In addition, if some services cannot be supported due to the resource changes, new SGs can be re-organized. As a result, self-organization and self-maintenance can be achieved to a certain level.

**The Problem Formulation of Resource Allocation under Harsh Conditions**

Based on the flexible resource management architecture proposed earlier, we design a new framework of environment-oriented resource allocation in response to the dynamics of the harsh environment. The framework leverages the environment-aware resource prediction to maximize the network utility function of interest.

To characterize the problem of resource allocation under the harsh environment, let us consider a network with \(D\)-dimensional resources supporting a total of \(L\) services. Meanwhile, we define the following three notations:

- **\(A\)** denotes the resource allocation matrix where the entry \(a_{l,d}\) represents the resource quantity allocated to the \(l\)th service on the \(d\)th resource.
- **\(W\)** is a predefined attention matrix with \(L\) rows and \(D\) columns, where the entry \(W_{l,d}\) characterizes the amount of attention that service \(l\) pays to the \(d\)th resource, and the sum of each row of \(W\) equals one for the normalization purpose.
- **\(r = [r_1, r_2, ..., r_D]\)**, a \(D\)-dimensional vector, denotes the amount of the available network resources, such as bandwidth and through-

\(^1\) The network stability under the harsh environment requires reliable transmission and access protocols. Hence, the alarm report transmission with very high reliability is necessary when an extreme event occurs.
put. Note that in the harsh environment, \( r \) is environment-dependent.

**A Toy Example:** For simplicity, consider \( L = 3 \) services and \( D = 2 \) types of the network resource, where

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A = \begin{bmatrix}
6 \text{ M/s} & 25 \text{ Mb} \\
10 \text{ M/s} & 40 \text{ Mb} \\
1 \text{ M/s} & 100 \text{ Mb}
\end{bmatrix}, \quad W = \begin{bmatrix}
0.3 & 0.7 \\
0.8 & 0.2 \\
0.4 & 0.6
\end{bmatrix}.
\]

The two columns of \( A \) have different units, representing the allocated rates and bandwidth in the service layer, and \( W \) indicates the preference levels, that is, the weights, of the corresponding allocated resources.

With the notations described above, we formulate the problem of resource allocation to maximize a sum of utility with network resource constraints. We define the utility function of interest as \( \psi_r(f, \theta) \), where \( f(\cdot) \) denotes a mapping function from the allocated resource quantity to the quality of service (QoS) requirements.\(^2\) The allocated resource quantity follows \( \sum_{L=1}^{L} a_i \leq r_d \) which denotes the resource budgets. Note that if \( f(\cdot) \) is convex, the problem can be efficiently solved by using the standardized inner-point method in polynomial time of the dimensions \( L \) and \( D \). However, if \( f(\cdot) \) is non-convex, which is very common in practice, the optimality cannot be efficiently achieved or even discovered. Hence, it is necessary to design an efficient method to explore the (sub-)optimality.

In our proposed architecture, incorporating the use of the vector \( r \) as a key, which is different from the conventional architectures. It can be enabled by the proposed environmental perception module in response to the harsh environment changes. To do it, we need to investigate how to well predict the available network resources based on the perception of the environmental conditions.\(^3\)

**The Proposed Method of Flexible Resource Allocation**

In this section, we focus on developing a solution to the problem defined earlier. For the purpose of initial investigation and for simplicity, we assume \( D = 1 \) for the rate/throughput only. As a result, we can drop off the foot index of \( d \), so \( a_j \) denotes the transmission rate of the \( j \)-th service, and \( r \) reduces to the scalar \( r \), which is environment-dependent. Also, \( \sum_{j=1}^{J} a_j \) is upper bounded by the system throughput as the function of the harsh environment.

First, we need to predict the system throughput, denoted by \( \hat{r} \), based on the environmental conditions. To do this, we leverage deep learning due to its superior capability to characterize the complicated underlying nonlinear mapping function. Specifically, we denote by \( \theta \) the vector comprising the environmental condition elements including temperature, dust, humidity, electromagnetic interference, and so on. Then we feed it as an input to a trainable model, and the output is the prediction, that is, \( \hat{r} = f(\theta) \) where \( f(\cdot) \) is the to-be-learned underlying mapping function. Since we aim to predict the available amount of each resource, the learning problem becomes a multivariate regression problem. While several models can be employed, we employ a convolutional neural network (CNN) for the initial research purpose.

Next, we introduce a method to effectively maximize the system utility. Considering that a centralized controller could be very expensive and fragile under extreme conditions, we assume the lack of cooperation and coordination among the services in the harsh environment. This naturally forms a non-cooperative scenario where each service needs to compete for the resource to optimize its own utility \( f(a_j) \). In such a scenario, it would be natural to employ game theory as an ingredient. Recognizing this key, we model the resource allocation as a non-cooperative power control game where the services are the game players and their actions are characterized by resource allocation matrix \( A \).

Note that in this game, if each service naively increases its transmission power \( p_j \) for a higher rate \( a_j \), more co-channel interference could be caused to other services. This in turn would suppress their rates and further induce them to continuously increase their own transmission power with diminishing or even no gains. On the other hand, if each service is very conservative in power consumption for interference control, it would also limit the rate. To characterize the trade-off between the two extremes, we introduce a pricing factor to the utility, which is regularized by a payment besides the transmission rate for each service, so the new utility can be updated as \( f(a_j) = \psi_f(a_j) - \lambda p_j \), where \( \lambda \) is the pricing factor and \( a_j \) is the rate function of \( p_j \). Moreover, the factor \( \lambda \) needs to be carefully designed. If \( \lambda \) is large, each service tends to improve its utility by using higher power; and if \( \lambda \) is large, the service would be more sensible about increasing power. In the harsh environment, since the throughput is affected by harsh conditions, dynamically adjusting the price factor according to the prediction \( \hat{r} \) would be expected.

By using the game theory model, the system can achieve the Nash equilibrium from which each rational service is unwilling to deviate. The method to achieve the Nash equilibrium is provided in Algorithm 1 for the resource allocation game. In addition, we also provide an overview of the solution in Fig. 2. The environmental conditions are sensed by the distributed sensors, then aggregated as the input of the environment-resource prediction model. The prediction model outputs the available network resources for scheduling. Note that the available resources are adjusted dynamically to address the environmental dynamic changes in the harsh environment. Then the resources are flexibly allocated to each service based on a game theory method with the pre-defined price factor. To this end, we achieve

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\(^1\) For instance, according to the Open System Interconnection (OSI) model, during the initial Transmission Control Protocol (TCP) handshake procedure, the max acceptable establishment delay is inherently associated with the failure probability of the connection establishment. The forms of \( f(\cdot) \) can be flexibly defined according to the service types, and some widely used forms include linear function, a step function, and non-linear functions.

\(^2\) The underlying mapping, if available, is usually non-linear and not straightforward because a few factors are coupled in the presence of various environmental conditions, such as the co-existence of dust, high humidity, and high temperature in industrial environments.
the environment-aware and self-optimization of the services.

**A Case Study: An Experiment and the Result**

To show the effectiveness of the proposed framework introduced earlier, we conduct a case study by applying the proposed solution to a wireless network in the presence of a power station under harsh conditions.

**The Considered Scenario**

The wireless network in the area around a large-scale power station usually suffers from higher noise level and lower transmission rate due to the presence of high electromagnetic interference (EMI). In particular, the high-power electronic devices, voltage load, and switch operations could significantly change the nearby field strength, causing high noise and interference to the receiver, thus further limiting the system throughput. Thus, the wireless network that still provides coverage and service applications in this scenario would need careful design in order to meet the QoS requirements.

In the experiment, we collected a dataset of measurements from China Unicom’s 5G cellular network close to a power station in the city of Qingdao in Shandong Province of China, where the strong EMI widely affects network performance. The dataset includes 416 data points, each with a total of 32 continuous environmental factors. These 32 factors consist of 30 EMI strength indicators denoted by the radiation power density on 30 uniformly distributed positions, the environment temperature, and the humidity. At each position, we used Rohde & Schwarz ESRP to measure the EMI strength on the 3.5 GHz–3.6 GHz frequency band. To capture abundant types of harsh environments, the measurements were collected every eight hours, that is, three times per day, for a total of non-consecutive 140 days from January to October 2019. After that, we manually adjusted the resource allocation method to maximize the throughput and then labeled each data point with the maximum throughput to represent the available throughput under the corresponding environment. Finally, in the lab, we labeled each data point with the corresponding throughput that was also collected from the network.

**Deep Learning for Available Resource Prediction**

As introduced previously, we employ deep learning to predict the maximum throughput for multiple environment factors. In particular, we implement a 1D CNN-based three-branch deep neural network, as shown in Fig. 3a, as we expect to capture the spatial correlation over the space. We tend to explore the global influence on network resources and to ignore the impact of measurement position. As the EMI strength indicators are sampled at 30 specific positions, we first adopt convolutional layers and a max pooling layer to extract overall features of environmental factors. To improve the ability of extracting multi-scale information, similar to [9], we build a three-branch CNN-based neural network. The three branches are deployed with different kernel sizes to enrich the diversity of receptive multi-scale features.

We demonstrate the structure of one branch in Fig. 3b. Each branch consists of five convolutional layers of the same size, each followed by a ReLU function as nonlinear activation. The number of kernels for each convolutional layer is 64, 64, 16, 16, and 4, respectively. A $4 \times 1$ max-pooling layer is added at the end of the branch to down-sample the data stream. Note that three branches are deployed with different kernel sizes to enrich the diversity of receptive multi-scale features. Specifically, $1 \times 1$, $3 \times 1$, and $5 \times 1$ 1D kernels, each with stride 1, and padding sizes 0, 1, and 2 are considered for the three parallel branches, respectively. As a result, the dimension of the signal right after the pooling is given by $8 \times 1 \times 4$ for each
branch. Next, we concatenate them along the last dimension, and then use 3 kernels with the size of $1 \times 1$ in another convolutional layer, and finally followed by a $24 \times 1$ fully connected layer to produce the prediction. Considering this is a regression problem, we employ the mean squared error as the loss function.

To train the model defined above, we choose the model hyper-parameters as: epoch number = 50, batch size = 8, the Adam optimizer [10] with $\beta_1 = 0.9$ and $\beta_2 = 0.999$, and learning rate = $4 \times 10^{-4}$, and we use the Xavier initialization [11] method to initialize the weights. Once the model is established, we split the dataset to non-overlapping training and testing subsets according to 75/25 percent splitting criteria; thus, 312 data points are used for training, and the other 104 data points are used for testing.

To evaluate the performance of the model defined above, we show the predicted results of the test dataset in Fig. 4a. We give the data samples in chronological order. It can be seen that the predictions well match with the ground truth in general. When rapid changes occur (data point index around 40 and 60), the model well predicts the throughputs. Indeed, we achieve 0.955 for the R-squared, 0.943 for the root mean squared error (RMSE), and 3.5 percent for the relative error.

![Figure 4a](image1.png)

**Figure 4.** a) The predicted throughput performance of the proposed environment-resource prediction model on the test dataset (sorted in an ascending order w.r.t. their ground truth); b) The utility of each device over the iterations of the algorithm; c) The average-SINR performance comparison between the proposed method and the method in [12]; d) The average-power performance comparison between the proposed method and the method in [12].

After obtaining $\hat{r}$, we substitute $r_d$ in the formulated problem with $\hat{r}$. Then our goal is to maximize the function defined as $u(a_l)$ in place of $f(a_l)$ by exploring the optimal network resource allocation. For the purpose of proof of concept, we consider a simple setting of $f(a_l) = a_l = B \log(1 + \text{SINR})$ where $B$ is the bandwidth, and SINR denotes the signal-to-interference-plus-noise ratio. Also, we assume the SINR only depends on the second-order statistics of the channels and the associated transmit power.4 For evaluation purposes, we also use SINR as the metric to evaluate the QoS. Recall that each service needs to adjust its transmission power to compete for higher transmission rate under the predicted throughput constraint. In addition to $f(a_l)$, the utility function of each device also considers its QoS, captured by the variable $p_l$.

For the purpose of initial investigation, we assume six services and co-channel interference existing in the network. To evaluate the performance of the proposed dynamic resource allocation method, we compare the proposed method to the one investigated in [12], which used a static resource allocation method, ignoring the dynamic environment constraints. The power of

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4 This assumption makes the problem easily tractable and can be used as a baseline for the proof of concept. In practice, it can also be realized by using the massive antenna arrays due to channel hardening. In terms of the required techniques to optimize the utility, admittedly, this assumption would allow a wider range of optimization tools in addition to the game-theory-based method that we propose in this article.
The ultra density of IoT devices in harsh environments, such as massive sensors and communication nodes in industrial production environments, brings challenges related to network congestion, networking, and storage architecture, and efficient data communication protocols under limited resources.

In Fig. 4b, we evaluate the power level of the six devices over the algorithm iterations to achieve the Nash equilibrium. It can be seen that the algorithm tends to converge after the sixth iteration. In fact, it is well known that the Nash equilibrium point based on the pure strategy always exists [13]. Thus, if the number of L is large, it might take longer for the algorithm to converge.

Finally, we evaluate the average SINR and average power. In particular, we calculate the average rate and the average SINR of the 104 data points in the test dataset. In Fig. 4c, it can be seen that the proposed scheme requires lower average power than the previous method by 22.6 percent on average; in Fig. 4d, the proposed algorithm achieves higher average SINR than the previous algorithm by 18.5 percent on average.

**FUTURE WORK DIRECTIONS**

As the initial investigation of the resource allocation under harsh conditions, we simplify the problem with a few assumptions that might not, if not impossible, fully characterize the environment dynamics. In this section, we suggest three components that we believe are worthy of further investigation.

**CHANNEL ACCESS MANAGEMENT**

The ultra density of IoT devices in harsh environments, such as massive sensors and communication nodes in industrial production environments, brings challenges related to network congestion, networking and storage architecture, and efficient data communication protocols under limited resources. These access mechanisms should be cost-effective and balance between the QoS requirements and the limited network resources. Also, due to the environment dynamics, the access management architecture should dynamically adapt to the resource status as well to meet the QoS requirements.

**EFFECTIVE ENERGY MANAGEMENT**

The harsh environment generally reduces the battery lifespan; thus, energy efficiency turns from an optional factor to a necessary design factor in order to provide reliable support. Ideally, the energy management method should consider power allocation, energy harvesting, and scheduling in dynamic networks [14]. In some remote environments, the devices have to be powered by battery due to the lack of power supply equipment. Hence, novel energy harvesting techniques would be necessary to extend the lifespan during the long unmanned periods.

**INTEGRATION OF SENSING AND COMMUNICATION CAPABILITY**

Due to network requirements such as high reliability, self-healing, and autonomy in harsh conditions, it is essential to enhance communication and networking capabilities by obtaining ambient environmental awareness. One popular idea is to integrate wireless sensing capability into wireless communication [15] so that the environmental resource management architecture could be extracted from the signal reflected from the surrounding scatterers. Currently, the coordination between resultant sensing and communication services is still widely under investigation, particularly the scheduling and resource allocation strategies of sensing and communications to maximize the overall network performance.

**CONCLUSION**

The harsh environment brings considerable challenges to network resource management. In this article, considering two main challenges, that is, the uncertainty of the environmental impact and the service requirement of a flexible adaptation mechanism, we propose a flexible resource management architecture that extended the functionalities of the physical plane, the resource plane, and the application plane from traditional architectures. Then, to incorporate the complicated environmental impact on network resources as an ingredient, we develop a deep-learning-based environment-resource prediction model to predict the resource constraints. With the predicted resource conditions, we finally schedule the network resources via game theory to maximize the system utility. We also present a case study to illustrate the effectiveness of the proposed architecture. Finally, we suggest three promising directions in network resource management, which are worthy of further investigation in the future.

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