ODiN : Enhancing Resilience of Disaster Networks through Regression Inspired Optimized Routing.

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***Abstract*—Reliable communication in disaster-hit areas is crucial for effective rescue and relief operations. This has encouraged the emergence of innovative, infrastructure-less, and ad hoc communication frameworks with the aim to keep Disaster Networks (DiNets) operational. However, emerging DiNet frameworks are still in their nascent stages. A vital challenge in ensuring seamless communication in harsh post-disaster scenarios is the design of robust routing algorithms. In this work, we elucidate the various constraints placed by post-disaster scenarios upon the design of routing mechanisms. We then implement an AllJoyn based DiNet prototype and gather real-time network data in an experimental site that resembles a disaster-hit zone. We subject gathered empirical data to *Regression Analysis*, create network models, and derive relationships between network parameters. The real-time regression equations of network parameter relationships serve as constraints in a high-level Mixed Integer Nonlinear Programming model named *ODiN*. The objective of ODiN is to offer optimal solutions to routing and next-hop relay selection in post-disaster scenarios. We demonstrate a significant reduction in convergence time while maintaining high accuracy through the use of ODiN.**

I. Introduction

Natural and man-made disasters not only cause immense loss of life and property but they also adversely impact ecology. Thus, development and deployment of resilient communication technologies, to mitigate the impact of disasters and to ensure prompt disaster response, is one of the pillars of the Sendai Framework under the aegis of *United Nations Office for Disaster Risk Reduction* [1].

Disaster networks (DiNets) are specifically designed to cater to critical and time-sensitive operations in disaster situations. DiNets are *proximity centric*, self-organizing, and decentralized which makes them resilient to failure in the face of challenging constraints posed by post-disaster scenarios.

Disaster events create unique and rather extreme ambient conditions for communication networks to be operational, which renders a top-down application of broad generalizations counter-productive and prone to failure. We resolve this challenge by making use Regression Analysis, a sub-set of Machine Learning techniques, to model empirical data from a DiNet prototype.

We make the following major contributions in this work.

- We describe the features of DiNets followed by the constraints experienced in routing in a post-disaster scenario.
- We implement an AllJoyn based DiNet prototype and conduct real-time experiments in a location which resembles a disaster-hit zone.
- We carry out Regression Analysis of empirical results to identify relationships between network parameters.
- We formulate a *Mixed Integer Non-linear Programming* (MINLP) model called ODiN that offers an optimal solution specific to the challenges in routing in DiNets.
- We then use the regression equations from the network model as constraints in ODiN formulation.
- Finally, ODiN performance is validated in terms of network throughput and *Convergence Time Reduced* (CTR).

Thus, the proposed *ODiN* model harnesses the real-time data from a post-disaster site to optimize routing in a DiNet. This novel approach ensures that the unique ambient conditions in the disaster-hit zone are adequately reflected in DiNet routing. To the best of our knowledge, no work on disaster and emergency networks has made use of Regression Analysis to optimize network performance.

II. Communication in post-disaster scenarios

In the aftermath of a severe disaster event, the existing communication infrastructure is disrupted, leaving the affected areas completely cut-off from the rest of the world. Thus, disaster mitigation efforts and time-critical rescue operations demand reliable communication solutions that require minimal configuration and are cost-effective. Disaster and emergency communication systems require a robust operation, interoperability, and continuity of communications.

A. Challenges in Conventional Disaster Networks

Traditionally, *continuity of communication* in disaster situations is achieved through alternative wireless technologies such as satellite phones, VSAT, Ham radio, *etc*. Recent developments have led to the merging of conventional modes of communication with technologies including 802.11 Wi-Fi, 802.16 WiMAX, *etc*. However, these technologies suffer from a wide variety of issues, a few of which are elucidated below. The conventional disaster communication systems involve expensive hardware, high installation times, and costly communication protocols often using satellite uplink/downlink. Limited interoperability between devices such as Push-To-Talk communications and VSAT/Sat Phones does not facilitate ease of data collection. Conventional systems are often deployed using theoretical disaster mobility models, which are predicated on assumed events and roles [2]. At times, a disaster sensor network may be available, but it has to be deployed before the disaster strikes, which is an expensive proposition.

The existing technologies also suffer from limited access and connectivity, overwhelmed services due to over-subscription, expensive equipment that has logistical constraints, and most importantly, limited information gathering and sharing tools. Besides, these networks are fragile and susceptible to frequent disruptions in the first few days of being set up [3], which are the most crucial days for rescue operations.

B. Next Generation Disaster Networks

Next-generation of DiNets includes ad hoc wireless and opportunistic wireless networks that facilitate real-time information exchange and efficient collaboration between rescue-personnel that are within each other's transmission proximity. Due to the increasing penetration of smartphones globally, there is a special emphasis on DiNets leveraging D2D communication. Frameworks such as AllJoyn [4], paradigms such as DTN [5], and technologies such as WiFi P2P [6] are being currently experimented to implement DiNets. It is not surprising that Android has released a Wi-Fi Direct (P2P) API for Android 4.0 and above to facilitate the development of disaster *Proximity Centric Networks* (PCNs) [7].

A PCN relies solely on the spatial proximity of devices that form a part of the network and wireless technologies that facilitate communication between devices in close proximity *e.g.*, Bluetooth, Wi-Fi Direct, *etc*. Thus, disaster PCNs overcome the need for seamless connectivity to the Internet, which is a remarkable shift from conventional disaster network designs and applications. Another benefit of employing a PCN is that latency inherent in data shared via the Internet will not be experienced in a disaster PCN.

C. Routing Constraints in a Disaster Scenario

Disaster hit zones are invariably characterized by extreme weather conditions, obstacles created by collapsed infrastructure, and harsh terrain which cause signal strength to be heavily attenuated. To facilitate a resilient and robust operation of a DiNet, SINR and RSSI received at a node must primarily determine next-hop choices for data transmission [8]. However, standard implementations of the traditional routing protocols which operate in the network layer, such as AODV or OLSR, seldom use SINR based information for the selection of next-hop node.

Thus, we contend that in disaster scenarios, signal strength and signal quality must primarily determine routing algorithms. In this work, we primarily focus on the signal strength and the impact of interference on transmissions by utilizing the empirically observed SINR values to formulate constraints for the ODiN optimal routing model.

Other important challenges to routing in post-disaster environments are listed below.

1) Signal strength and the impact of interference on transmissions quantified by SINR.
2) Harness the availability of multiple radios.
3) Robustness and resilience, *e.g.,* recovery from a failed data transmission due to link disruption.
4) Energy efficient protocols, as device battery is a scarce resource in disaster scenarios.
5) Interoperability, *i.e.,* ability to rout over heterogeneous devices and RATs.
6) Maximum number of intermediate nodes that don't adversely affect network performance.
7) Node specific priority to data uplink or downlink.
8) The trade-off between data/link redundancy and energy consumption and space requirement.
9) Hostile and inaccessible terrain. The impact of terrain on signal strength can significantly shape the next-hop choice.

We attempt to address several of these challenges in the proposed ODiN model.

Fig. 1: AllJoyn Dinet prototype.

III. AllJoyn Disaster Network Prototype

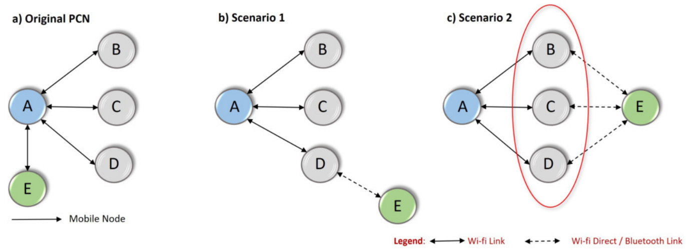
AllJoyn [9] is an open-source framework that is agnostic to underlying radio access technology and facilitates the integration of heterogeneous client-devices. AllJoyn performs services such as participant device discovery, attachment, session management, *etc.,* between participant mobile devices. A detailed discussion on AllJoyn routing and implementation is presented in [4].

A. Experiment Setup and Deployment Site

We implement a 5-node AllJoyn DiNet illustrated in Figure 1. A toy model of routing in a dynamic PCN with mobile nodes is presented in Figure 2 (a). The four laptops run on the Ubuntu 16.04 LTS operating system while the Google Nexus 5 smartphone runs on Android KitKat 4.4.4. The laptops serve as stationary nodes stationed at different locations while the smartphone is mobile and transmits data to the other nodes. The DiNet is realized through a *Wi-fi ad hoc network* with Extended Basic Service Set Identity (ESSID) "DisaNet", with the help of *Independent Basic Service Set* or IBSS mode of Wi-Fi in $2.4GHz$ over the same Wi-Fi channel.

Due to the presence of rubble and collapsed structures, disaster-hit zones suffer severely from *multi-path fading* as multiple copies of a transmission signal interfere at the receiver [10]. For this reason, we choose an under-construction building site for DiNet deployment, as shown in Figure 2 (b). The presence of semi-constructed structures and obstacles such as rubble mounds on the pathways *etc.,* creates some semblance of a disaster-hit zone.

The mobile node transmits files of three sizes *viz.,* 1MB, 4MB, and 10 MB, at spatial intervals of $5m$. The rationale is



(a) Routing Toy Model.

(b) Experiment sites.

Fig. 2: AllJoyn DiNet Deployment

to replicate real-world disaster data which typically includes three major file types *viz.,* images of low pixel-density, high-resolution images, and low-resolution videos, and high-quality videos.

B. Preliminary Analysis of Network Data

We gather a variety of real-time network data for the DiNet prototype, including network throughput, latency, and signal strength experienced by the mobile node. We observe that DiNet performance is heavily dependent on the signal strength, which varies substantially with distance. The peculiar challenges of disaster environment, such as obstacles and collapsed structures, make the impact of distance on received signal strength even more strong and somewhat erratic. For example, while small files (1MB) are transmitted as long a connection exists, larger files (4MB and 10MB) experience transmission failures when signal strength drops below -67dBm.

Another aspect is power consumption, the rate of which is accelerated as inter-nodal distance increases. Distance has an extremely adverse impact on battery life in disaster scenarios. This can be understood by the fact that to transmit a $1MB$ file, the battery drain increases by a factor of 60 at $75m$ as compared to that at $5m$. Likewise, the end-to-end packet latency increases by a factor of 42 at the two inter-nodal distances.

We subject the gathered empirical data to regression analysis to determine the relationship between inter-nodal distance and network parameters.

IV. Regression Analysis of Network Data

Regression Analysis is a statistical tool and a sub-set of Machine Learning techniques which are used to ascertain the relationship between tangible or intangible variables in a system [11]. In any scientific experiment one or more *independent variables* are manipulated, and the corresponding change in a *dependent variable* is observed. A Regression Model (RM) is used to explore whether a *statistically significant* relationship exists between a dependent variable and one or independent variables. This makes Regression Analysis a desirable tool not only for modeling and fitting data but also for causal analysis.

Our goal is to determine a relationship between network parameters from the empirical DiNet data. Thus, we consider Linear and Polynomial Regression techniques which assess the *statistical significance* of the relationship in terms of *p-values* (p-val). They also offer insights into the relationship between network parameters by stating the degree to which *variation* in response variable can be justified due to the change in the independent variable through the *R-sq* of the RM.

Relationships between network parameters may be non-linear, and Polynomial Regression successfully meets this requirement by *fitting* non-linear network data on a curve. Finally, P-values and R-Sq are not feasible in non-linear regression techniques, which makes them unsuitable for our objectives. P-value or the *level of risk* of a model is signified by α, and the normally accepted P-value is $\alpha = 0.05$. However, there has been a greater debate on the use of P-values in determining the accuracy of the models [12] and to assuage these concerns we consider $\alpha = 0.001$, which offers *highly statistically significant* models and substantially reduces the probability of misinterpretation.

Having identified that the inter-nodal distance is the primary determinant of network performance in terms of signal strength, throughput, delay, and battery-life, we carry out linear and polynomial regression analysis with inter-nodal distance as the predictor variable (X), and network metrics as the response variables (Y). We select RMs with $P-value \leq 0.001$ and the highest R-Sq values as they produce regression equations that best explain the relationship between response and predictor network variables. The Network Parameter Relationships (NPRs) are presented in Table I.

TABLE I: Regression Analysis of DiNet Data.

Parameter (Y)	**R-sq**	**Regression Equation***
Signal Strength	86.94	Y = - 47.93 - 0.5973 X + 0.002923 X^2
Throughput†	88.92	Y = 17.56 - 0.4790 X + 0.003370 X^2
Battery Drain†	87.97	Y = 0.05925 - 0.004742 X + 0.000129 X^2
Delay†	79.34	Y = 1185 - 124.7 X + 4.302 X^2

* Inter-nodal distance is the predictor (X) and network parameter is the response (Y).
† Parameter values considered are for 1MB file.

Regression Models for all network parameters have high R-sq values, which demonstrate a significant impact of inter-nodal distance on network performance. The NPR equations are derived from empirical data and represent the actual ambient environment of a disaster network. We argue that using NPR equations in network optimization will not only reflect the network conditions in the optimization model but also reduce convergence-times of optimal results [13]. DiNets are time-critical as real-time information is crucial to relief and rescue efforts. In such circumstances, reduced convergence-times in network optimization are highly preferable.

A DiNet optimization may involve several parameters *viz.,* signal strength, network capacity, energy efficiency, delay tolerance, and reliability in data transmission. As discussed in SubsectionII-C, in this work, we focus on signal strength using the empirically derived NPR of signal strength in network optimization.

V. Optimal Routing for Disaster Networks

We now formulate a high-level MINLP model called *ODiN* to offer an optimal solution to multi-hop routing in disaster networks and ensure maximal throughput. The ODiN model is proposed with the objective of maximizing network capacity through a routing mechanism predicated on signal strength, which makes use of a theoretical SINR constraint. Thereafter, we replace the theoretical constraint of signal strength with the empirically derived NPR equation of signal strength from Table I. We then contrast the performance of two versions of ODIN. While formulating ODiN, several other constraints specific to disaster scenarios have also been considered.

In addition, ODiN also makes two more considerations relevant to disaster networks :

- Spectrum is scarce and should be reused.
- The constraints should be applied to new ad hoc links created through Wi-Fi Direct, Bluetooth, *etc*.

A. Theoretical ODiN Model (ODiN$_T$)

To maximize the overall throughput in the disaster network, we choose optimal ad hoc (Wi-Fi direct, Bluetooth, *etc.*) links and allocate the unlicensed spectrum chunk effectively to these links and tune the uplink power for these links. We assume that the DiNet nodes are deployed in a random topology, and at least one of the nodes is mobile. Let M denote the set of nodes deployed in the DiNet. Let I = { i_1, i_2, . . . , i_n } be the set of relay (intermediate) nodes and J = { j_1, j_2, . . . , j_n } be the set of mobile (moving) nodes. Let D_{ij} be an ad hoc Wi-Fi direct link between nodes i and j, and C = { c_1, c_2, . . . , c_n } denote the set of available unlicensed channel in the 5GHz band. The objective of maximizing the throughput of the DiNet through optimal routing is expressed in Equation (1), where B represents the DiNet bandwidth. [1]

$$max(B \times log(1 + SINR_{ij}) \tag{1}$$

A binary variable, X_{ij} whose value is 1 if i is connected to j through the ad-hoc link, else 0, where $i \in I$, $j \in J$.

$$\begin{cases} X_{ij} = 1 & \text{for} \qquad \forall i \in I, \forall j \in J \\ X_{ij} = 0 & \text{else} \end{cases}$$

[1]An alternate optimization goal can be the minimization of the maximum power ($min(max(p_i^z))$ consumed by ad hoc links with the constraints identical to that of ODiN.

The upper bound on the maximum number of relay nodes permitted by the DiNet is given by,

$$\sum_{j \in J} X_{ij} \leq \alpha \qquad \forall i \in I \tag{2}$$

The packet flow between relay node i and the next-hop node j should be non-negative,

$$X_s(i, j) > 0 \tag{3}$$

We assume that Wi-Fi operates in the orthogonal frequency division multiple access (OFDMA) mode (*i.e.,* 802.11 ax), and possesses scheduling capability in the given transmission time (*i.e.,* TXOP). Through the new concept of Basic Service Set (BSS) Coloring, 802.11ax ensures an efficient spatial reuse of the spectrum similar to that in cellular LTE [14]. We place a limit on the maximum number of ad-hoc Wi-Fi direct links in a given TXOP.

$$\sum_{i \in I} \sum_{j \in J} X_{ij} = \beta \qquad \forall j \in J \tag{4}$$

The values of α and β can be fine-tuned as per network requirements. The binary variable Q_{ij}^z is 1 when relay node i and mobile node j communicate through the spectrum z, and 0 otherwise, where $i \in I$, $j \in J$ and $z \in Z$. Here, η denotes the maximum number of spectrum chunks which can be allocated to each Wi-Fi direct link.

$$\begin{cases} Q_{ij}^z = 1 & \text{for} \qquad \forall i \in I, \forall j \in J \\ Q_{ij}^z = 0 & \text{else} \end{cases}$$

$$\sum_{z \in Z} Q_{ij}^z \leq \eta \times X_{ij} \qquad \forall i \in I, \forall j \in J \tag{5}$$

Further, each node in the DiNet may have multiple radios. In equations below, u_{min} and u_{max} represent the minimum and maximum number of radios installed on a node, respectively.

$$\sum X_i \geq u_{min} \tag{6}$$

$$\sum X_i \leq u_{max} \tag{7}$$

A binary variable, L_i^z whose value is 1 if node i is using spectrum z for Wi-Fi direct link else 0, where $i \in I$, $z \in Z$.

$$\begin{cases} L_i^z = 1 & \text{for} \qquad \forall i \in I, \forall z \in Z \\ L_i^z = 0 & \text{else} \end{cases} \tag{8}$$

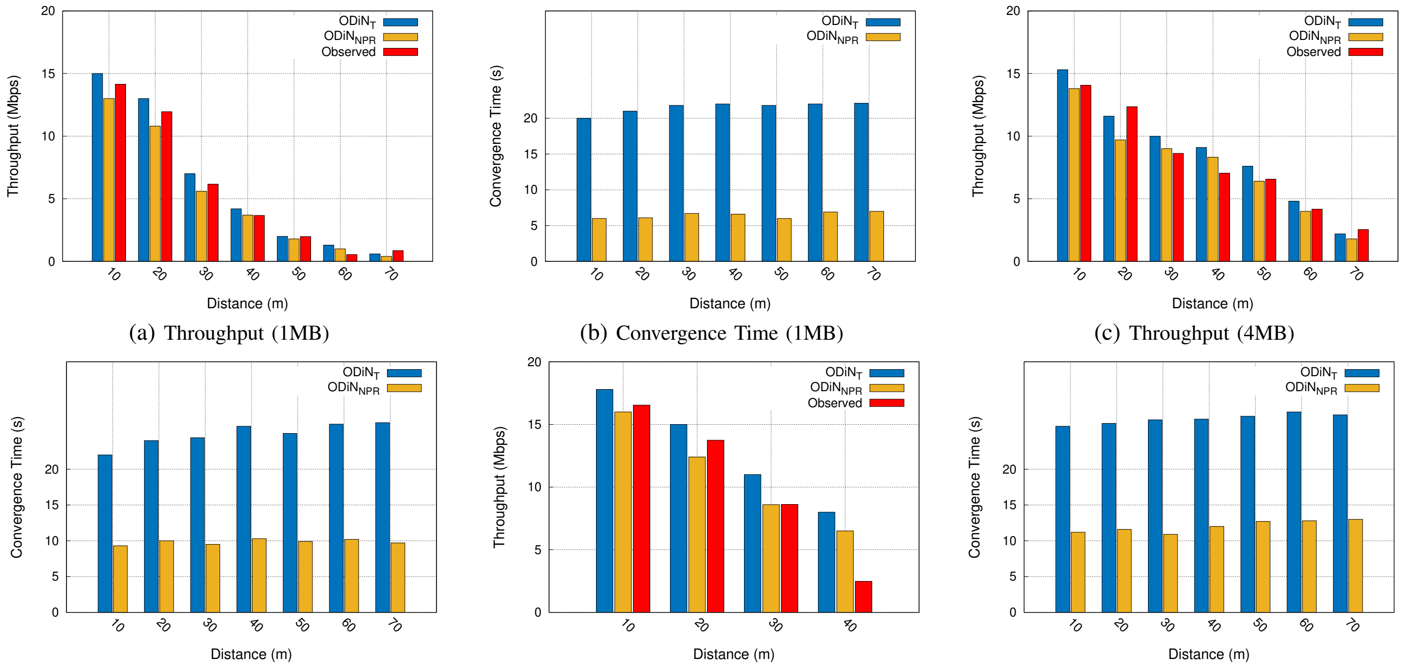
L_i^z is set to be 1 if relay node i is using the spectrum z. The Equation (8) is ensured by Equation (9).

$$L_i^z = Q_{ij}^z \qquad \forall i \in I, \forall j \in J, \forall z \in Z \tag{9}$$

Equation (10) guarantees that the normalized power emitted by relay node i in spectrum z is 0 when not being utilized by node i.

$$p_i^z \leq L_i^z \qquad \forall i \in I, \forall z \in Z \tag{10}$$

P_{max}^w denotes the maximum power of a transmitting node (*e.g.,* WI-Fi AP/hotspot). Upon solving the ODiN formulation,



(a) Throughput (1MB) (b) Convergence Time (1MB) (c) Throughput (4MB)

(d) Convergence Time (4MB) (e) Throughput (10MB) (f) Convergence Time (10MB)

Fig. 3: Evaluation of ODiN

transmission power of a relay node i in a spectrum chunk z is calculated as $p_i^z \times P_{max}^w$, where the power value (in watts) lies in the range of $0 \leq p_i^z \leq 1$. The below equation restricts the number of uplink connections a mobile node can establish and the transmit power for the uplink tranmission is in the range of $0 \leq p_i^z \leq 0.1$

$$\sum_{i \in I} X_{ij} \leq n \qquad \forall j \in J \tag{11}$$

The L.H.S. of Equation (12) is the $SINR_{ij}$ received at the mobile node j due to transmissions from relay node i, and N_0 represents the system noise. To ensure a reliable connection, the $SINR_{ij}$ of each Wi-Fi direct link is maintained above a predefined threshold λ_j, which may vary across mobile nodes.

$$\frac{Inf \times (1 - Q_{ij}^z) + G_{ij} p_i^z P_{max}^w}{N_o + \sum\limits_{w \in W_k} G_{wj} P_{max}^i + \sum\limits_{i' \in I \setminus i} G_{i_j'} p_{i'}^z P_{max}^w} \geq \lambda_j \qquad \forall i \in I, j \in J, z \in Z \tag{12}$$

Here, W_k is the set of all nodes using the spectrum z in a given TXOP duration. Similarly, G_{wj} is the channel gain from the other DiNet node w to j (operating on the same spectrum chunk), G_{ij} is the channel gain from i to j.

The use of $Inf \times (1 - Q_{ij}^z)$ ensures that if $Q_{ij}^z = 0$, then $Inf \times (1 - Q_{ij}^z)$ amounts to a very large value, which allows for the expression to be conveniently ignored. Through the virtual infinite value Inf, Equation (12) ensures that all relay nodes provide a minimum $SINR_{th}$ to a particular mobile node. ODiN implementation will be impractical without the SINR consideration through Inf. The Equation (12) can be rewritten as follows,

$$SINR_{ij} \leq \frac{Inf \times (1 - Q_{ij}^z) + G_{ij} p_i^z P_{max}^w}{N_o + \sum\limits_{w \in W_k} G_{wj} P_{max}^i + \sum\limits_{i' \in I \setminus i} G_{i_j'} p_{i'}^z P_{max}^w} \qquad \forall i \in I, \forall j \in J, \forall z \in Z \tag{13}$$

Finally, the ODiN capacity optimization model is formulated as follows,

$$max(Blog(1 + SINR_{ij}) \text{ s.t., } (2), (4), (5), (9), (10), (11), (13).$$

B. Regression Inspired ODiN (ODiN$_{NPR}$)

We propose a novel approach wherein we replace the theoretical constraints in an optimization model with *Network Performance Relationships* derived through Regression Analysis of empirically observed data. In the current implementation of ODiN, we replace the computationally intensive theoretical SINR constraint in (13) with the regression equation for SINR presented in Table I in the following equation.

$$max(SINR_{ij})$$

Equation (14) reflects the NPR between inter-nodal distance and SINR.

$$SINR_{ij} = -47.93 - 0.5973 X_{ij} - 0.002923 X_{ij}^2 \tag{14}$$

Finally, the regression inspired ODiN model is formulated as, $max(SINR_{ij})$ s.t., $(2), (4), (5), (9), (10), (11), (14)$.
By solving ODiN$_{NPR}$, we achieve the following:

- Optimal relay node selection & reduced convergence time through regression analysis.
- Optimal assignment of spectrum z to each established ad hoc link, especially the Wi-Fi direct links.
- Minimization of the power emitted by a mobile node.
- Leveraging empirical data to guarantee signal quality above threshold for each mobile node being served by the relay nodes.

VI. Simulation, Results, and Evaluation

ODiN$_T$ and ODiN$_{NPR}$ are applied to the AllJoyn DiNet prototype, and optimal solutions are generated by solving the models with the help of GAMS CPLEX solver through its branch and bound framework [15]. The output of GAMS solver serves as input to the system model simulated on MATLAB, which visualizes signal strength and throughput. ODiN is a high-level generic model that considers several factors, such as transmission power, optimal spectrum splitting, *etc*.

Since the objective of the experiment is to validate ODiN, we focus on network capacity and fix other values in the model as they were in the DiNet implementation. For example, Maximum Transmission Power for the nodes was set at $22dBm$, in line with device configurations. Some constraints were relaxed, *e.g.,* only one user was assumed to be active at a given time, so there was no splitting of the spectrum. However, the optimal model is fully capable of addressing realistic conditions.

The experimental values from DiNet implementation are evaluated against the theoretical results generated from the two ODiN variants and presented in Figure 3. We consider throughput for the three file sizes transmitted in the experiments. Likewise, *Convergence Time* (CT) taken to solve for the optimal next-hop relay is calculated for ODiN$_T$ and ODiN$_{NPR}$, and the CTs for both are compared. It can be discerned from Figure 3 that ODiN$_{NPR}$ outperforms ODiN$_T$. When compared to ODiN$_T$, the average % convergence time reduction (CTR) by ODiN$_{NPR}$ for 1MB, 4MB, and 10MB files is 69.94%, 60.36%, 55.55%, respectively.

A cost-benefit analysis reveals that despite remarkable CTR performance by ODiN$_{NPR}$, it is also 18.2%, 21.93%, and 34.29% more accurate than ODiN$_T$ on an average for 1MB, 4MB, and 10MB files, respectively. If we consider the deviation from experimentally observed DiNet throughput, ODiN$_{NPR}$ shows an average deviation of 11.68% for 4MB file transmissions, which is tolerable.

Another aspect is the impact of distance on the Convergence Time of ODIN models. As observed in empirical results earlier, the simulation results demonstrate a constant reduction in Throughput as the inter-nodal distance increases. However, as the distance increases no corresponding increase in CT is observed in the proposed ODIN models. This implies that the computational resources required for optimization remain almost constant, and the energy consumption does not rise significantly with distance. This is ideal for a disaster network scenario where low CTs for next node selection and minimal battery drain is desirable.

We observe that the use of regression equations as constraints significantly improves network optimization in disaster scenarios, in terms of both, Convergence Time and Accuracy.

VII. Conclusion and Future Work

Introducing constraints derived from Regression Analysis of real-time network data in the ODiN optimization model substantially reduces the convergence time while maximizing network capacity. Optimal results offered by ODiN are consistent with the empirical results, which lends credibility to the proposed model and the novel approach of using empirically derived regression equations as constraints.

VIII. Acknowledgement

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