KORA: A Framework for Dynamic Consolidation & Relocation of Control Units in Virtualized 5G RAN
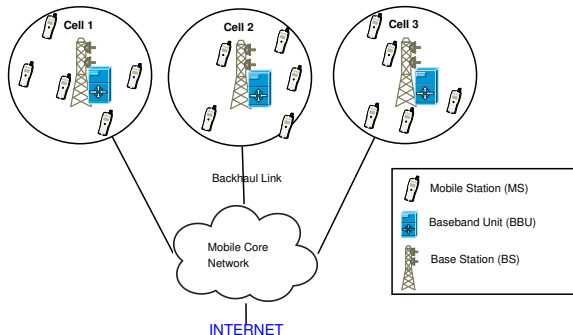
Debashisha Mishra, Himank Gupta, **Bheemarjuna Reddy Tamma** and Antony Franklin A

Networked Wireless Systems (NeWS) Lab
Dept. of Computer Science and Engineering
Indian Institute of Technology Hyderabad, INDIA

IEEE ICC 2018 SAC Symposium on
Cloud Communications and Networks Track
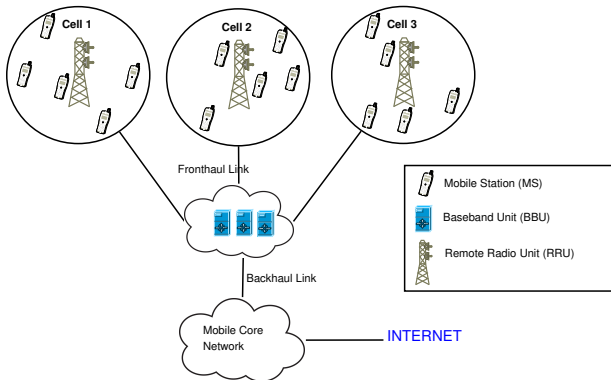21st May, 2018
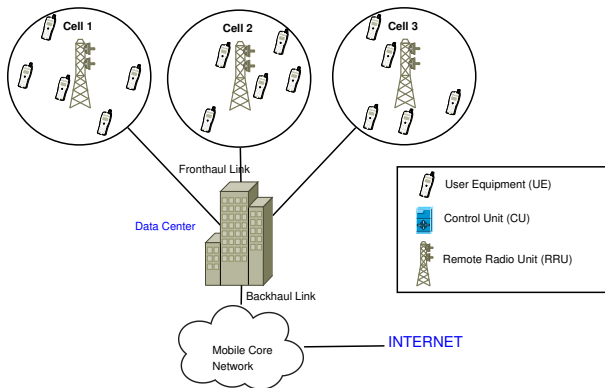
Traditional RAN: 1G → 4G

- Collocated RF & Baseband (inc. protocol stack) of Base Station (BS) at Cell sites
- Dedicated and proprietary hardware and software

RAN Evolution to Centralization: 4G+

- RF and Baseband components spread at different locations
- Baseband functions from cell sites are pooled in a central office

RAN Virtualization : Cloud RAN

- RF and Baseband components spread at different locations
- Baseband functions are virtualized in a cloud data center
- Seen in 5G architectures from 3GPP & in IEEE NGFI

Multiplexing Opportunities of CUs in Cloud DC
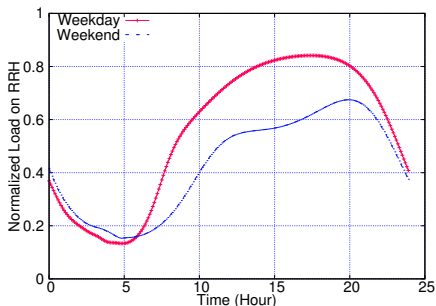

- Multiplexing gain by sharing of resources as in *cloud computing*
- Tidal traffic pattern provides an opportunity to multiplex CU compute load on GPP servers

Spatio-temporal Pattern of Traffic Load
Temporal Dynamics

Load on individual base stations do not follow any periodicity, however the trend is consistent with diurnal activity patterns of human beings.

Spatio-temporal Pattern of Traffic Load
Spatial Dynamics

The residential zones tend to be active in off-hours (nights, weekends and holidays) while business or office areas are active during daytime in weekdays.

Figure: Weekend Spatial Plot

Figure: Weekday Spatial Plot

KORA: Integrated & shared computing framework for Cloud RAN in 5G

- CUs can be realized on a hypervisor based virtual machine (VM) or containerized LXC/Docker instances
- Depending upon fronthaul transport network, a more flexible distribution of baseband functions & higher layers of stack b/w RRU and CU is feasible
- Based on amount of real-time user traffic generated at RRU (aka DU), corresponding CU's computational resource requirement may grow ($\to$ relocation) or shrink ($\to$ consolidation) dynamically

System Notations

System Notations

- $\mathcal{N} \rightarrow$ Set of RRUs, $\mathcal{N} = \{1, 2, ..., N\}$
  $\mathcal{V} \rightarrow$ Set of CUs, $\mathcal{V} = \{1, 2, ..., V\}$
  $\mathcal{M} \rightarrow$ Set of Compute Servers/Nodes, $\mathcal{M} = \{1, 2, ..., M\}$

System Notations

- $\mathcal{N} \rightarrow$ Set of RRUs, $\mathcal{N} = \{1, 2, ..., N\}$
  $\mathcal{V} \rightarrow$ Set of CUs, $\mathcal{V} = \{1, 2, ..., V\}$
  $\mathcal{M} \rightarrow$ Set of Compute Servers/Nodes, $\mathcal{M} = \{1, 2, ..., M\}$
- $N = V$ and $M \leq V$.

System Notations

- $\mathcal{N} \rightarrow$ Set of RRUs, $\mathcal{N} = \{1, 2, ..., N\}$
  $\mathcal{V} \rightarrow$ Set of CUs, $\mathcal{V} = \{1, 2, ..., V\}$
  $\mathcal{M} \rightarrow$ Set of Compute Servers/Nodes, $\mathcal{M} = \{1, 2, ..., M\}$
- $N = V$ and $M \leq V$.
- Let $l_v =$ Computer load of CU $v \in \mathcal{V}$ in FLOPS.

System Notations

- $\mathcal{N} \rightarrow$ Set of RRUs, $\mathcal{N} = \{1, 2, ..., N\}$
  $\mathcal{V} \rightarrow$ Set of CUs, $\mathcal{V} = \{1, 2, ..., V\}$
  $\mathcal{M} \rightarrow$ Set of Compute Servers/Nodes, $\mathcal{M} = \{1, 2, ..., M\}$
- $N = V$ and $M \leq V$.
- Let $l_v =$ Computer load of CU $v \in \mathcal{V}$ in FLOPS.
- Let $L_{max} =$ Maximum capacity of computer node in FLOPS.

System Notations

- $\mathcal{N} \rightarrow$ Set of RRUs, $\mathcal{N} = \{1, 2, ..., N\}$
  $\mathcal{V} \rightarrow$ Set of CUs, $\mathcal{V} = \{1, 2, ..., V\}$
  $\mathcal{M} \rightarrow$ Set of Compute Servers/Nodes, $\mathcal{M} = \{1, 2, ..., M\}$
- $N = V$ and $M \leq V$.
- Let $l_v =$ Computer load of CU $v \in \mathcal{V}$ in FLOPS.
- Let $L_{max} =$ Maximum capacity of computer node in FLOPS.
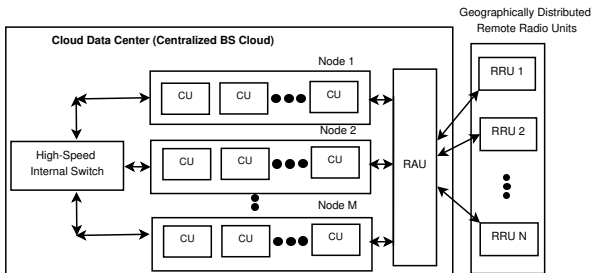- Let $C_m =$ Capacity of compute node $m \in \mathcal{M}$.

System Notations
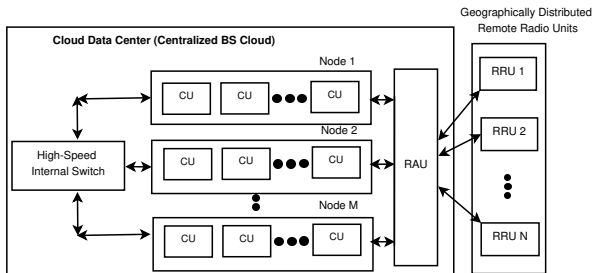

- $\mathcal{N} \rightarrow$ Set of RRUs, $\mathcal{N} = \{1, 2, ..., N\}$
  $\mathcal{V} \rightarrow$ Set of CUs, $\mathcal{V} = \{1, 2, ..., V\}$
  $\mathcal{M} \rightarrow$ Set of Compute Servers/Nodes, $\mathcal{M} = \{1, 2, ..., M\}$
- $N = V$ and $M \leq V$.
- Let $l_v =$ Computer load of CU $v \in \mathcal{V}$ in FLOPS.
- Let $L_{max} =$ Maximum capacity of computer node in FLOPS.
- Let $C_m =$ Capacity of compute node $m \in \mathcal{M}$.
- Let $\delta t =$ Time interval (epoch) for continuous traffic measurements
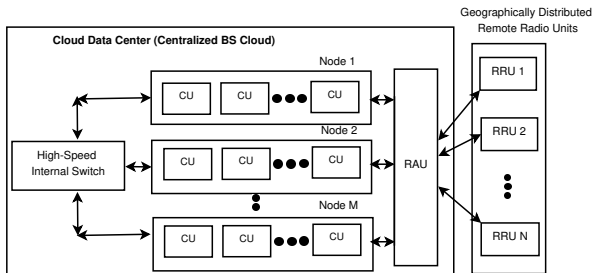
System Notations

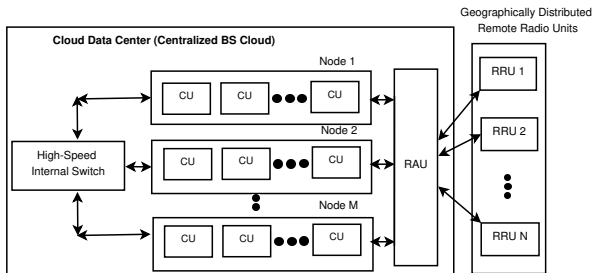

- $\mathcal{N} \rightarrow$ Set of RRUs, $\mathcal{N} = \{1, 2, ..., N\}$
  $\mathcal{V} \rightarrow$ Set of CUs, $\mathcal{V} = \{1, 2, ..., V\}$
  $\mathcal{M} \rightarrow$ Set of Compute Servers/Nodes, $\mathcal{M} = \{1, 2, ..., M\}$
- $N = V$ and $M \leq V$.
- Let $l_v =$ Computer load of CU $v \in \mathcal{V}$ in FLOPS.
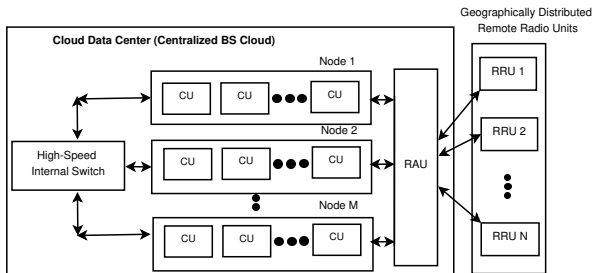- Let $L_{max} =$ Maximum capacity of computer node in FLOPS.
- Let $C_m =$ Capacity of compute node $m \in \mathcal{M}$.
- Let $\delta t =$ Time interval (epoch) for continuous traffic measurements
- Let $T =$ Traffic Measurement Window (≤ 24 Hours), $0 \leq T \leq 24$

Research Problem

Problem Statement

Determine the minimum possible number of compute nodes needed to serve 'N' RRUs in each time interval δt with minimum disruption to users considering spatio-temporal traffic dynamics

Expected Solution

A flexible allocation and relocation schedule (Allocation Matrix) for CUs in each time interval δt that optimizes the aforementioned objective

- Architectural Considerations
  - 1-to-1 mapping between RRU and CU
  - Many-to-1 mapping between CUs and Compute Node
- Performance Metrics
  - Number of active computer nodes/servers
  - User Service Continuity
  - Scalability
  - Responsiveness

Traffic Model

- Cell load at RRU r at time t, $l_r(t)$ is given by,

$$l_r(t) = \sum_{u \in U_{\{r\}}(t)} \frac{No\_of\_PRBs\_Allocated\_to\_user\_u}{No\_of\_Available\_PRBs\_in\_cell} \quad (1)$$

- Weighted score metric ws_r gives a unified value by quantifying active user flows,

$$ws_r = (w_1 \times N\_ngbr) + (w_2 \times N\_voice + \qquad \qquad (2)$$
$$w_3 \times N\_conv + w_4 \times N\_game + w_5 \times N\_stream)$$

Notation	Definition	Weight
(N_voice)	GBR - Voice traffic flows	0.30
(N_game)	GBR -Real-Time Gaming	0.25
(N_conv)	GBR -Conversational Videos	0.20
(N_stream)	GBR - Live Streaming Video	0.15
(N_ngbr)	Non-GBR data flows	0.10

Processing Load Model

- The baseband processing time per subframe in microsecond $(proc(u, t))$ on a GPP server is given by,

$$proc(u, t) = r_{base} + p_{base} + u(mcs, prb) + u(r) \qquad (3)$$

Notation	Definition
r_{base}	Constant cell offset
p_{base}	Platform dependent constant
$u(mcs, prb)$	User dependent processing
$u(r)$	Other user processing task

- We use FLoating point Operations Per Second (FLOPS) [1] as a measure of computer performance. Let us denote the maximum FLOPS limit as L_{max}. The compute load $l_v(t)$ for CU $v \in \mathcal{V}$ in FLOPS serving RRU $r \in \mathcal{N}$ is given by,

$$l_v(t) = L_{max} \times \left(\sum_{u \in U_{\{r\}}(t)} proc(u, t) \right) \qquad (4)$$

---

[1] For example, in double precision convention, a general purpose Intel CPU core can perform four floating point operations per CPU cycle. Consider a single core Intel CPU of 2 GHz frequency, which denotes that the CPU is capable of 2 billion CPU cycles per second, thus resulting in a theoretical performance of $(2 \times 10^9 \times 4) = 8$ GFLOPS.

Cost Models

- The power consumption of a compute server with CPU utilization of u is given by,

$$P_u = P_{idle} + (P_{cap} - P_{idle}) \times u \qquad (5)$$

As per SPECpower benchmark[2], average power consumption for a standard GPP server with CPU utilization of 100% is approximately 259 Watt.

---

[1] http://www.spec.org/power_ssj2008/results/res2010q4/

[2] Performance and Energy Modeling for Live Migration of Virtual Machines, https://doi.org/10.1007/s10586-011-0194-3

Cost Models

- The power consumption of a compute server with CPU utilization of u is given by,

$$P_u = P_{idle} + (P_{cap} - P_{idle}) \times u \qquad (5)$$

As per SPECpower benchmark[2], average power consumption for a standard GPP server with CPU utilization of 100% is approximately 259 Watt.

- The additional energy spent (in Watt-second) on live migration (reconfiguration)[3] is given by,

$$E_{Reconf} = 0.512 \times S + 20.165 \qquad (6)$$

where S is the data volume (in MB) of CU to be transferred from source to target server to realize live migration of CU.

---

[1]http://www.spec.org/power_ssj2008/results/res2010q4/

[2]Performance and Energy Modeling for Live Migration of Virtual Machines, https://doi.org/10.1007/s10586-011-0194-3

Integer Linear Programming (ILP) Formulation

Notation	Definition
l_v	Compute load at CU $v \in \mathcal{V}$
C_m	Capacity of compute server $m \in \mathcal{M}$
z_m	1 if compute server $m \in \mathcal{M}$ is active; otherwise 0
y_{vm}	1 if CU v is active on compute server m; otherwise 0
A_t	Allocation matrix of all CUs to compute servers at time t
$A_t(v)$	Allocation of CU $v \in \mathcal{V}$ to a compute server at time t
$cost_{vm}$	Additional energy cost incurred in relocation of CU $v \in \mathcal{V}$ to compute server $m \in \mathcal{M}$
ρ_v	Normalized score of $v \in \mathcal{V}$ indicating relocation impact

Objective Function : *Minimize*

$$\left(\sum_{m=1}^{M} (z_m \times cost_m) \right) + \left(\sum_{\substack{v \in \mathcal{V}, m \in \mathcal{M}, \\ \text{such that} \\ m \neq A_{(t-1)}(v)}} (\rho_v \times y_{vm} \times cost_{vm}) \right) \tag{7}$$

Constraints :

$$\sum_{m=1}^{M} y_{vm} = 1, \quad \forall v \in \mathcal{V} \tag{8}$$

$$\sum_{v=1}^{V} (y_{vm} \times l_v) \leq (C_m \times z_m), \quad \forall m \in \mathcal{M} \tag{9}$$

Numerical illustration
Server Capacity $= 100\%$, $\delta t = 1$, $T = 4$

CU	l_v
1	40
2	46
3	57
4	82
5	22

$t = 0$

Numerical illustration
Server Capacity $= 100\%$, $\delta t = 1$, $T = 4$

CU	l_v
1	40
2	46
3	57
4	82
5	22

$t = 0$

$t = 0$

Numerical illustration
Server Capacity $= 100\%$, $\delta t = 1$, $T = 4$

CU	l_v
1	40
2	46
3	57
4	82
5	22

$t = 0$

S1   **S2**   **S3**

46		22
40	82	57

$t = 0$

	S1	**S2**	**S3**	**S4**
C1	1	0	0	0
C2	1	0	0	0
C3	0	0	1	0
C4	0	1	0	0
C5	0	0	1	0

A_0

Numerical illustration
Server Capacity $= 100\%$, $\delta t = 1$, $T = 4$

CU	l_v
1	40
2	46
3	57
4	82
5	22

$t = 0$

CU	l_v
1	70
2	20
3	30
4	35
5	50

$t = 1$

$t = 0$

1	0	0	0
1	0	0	0
0	0	1	0
0	1	0	0
0	0	1	0

A_0

Numerical illustration
Server Capacity $= 100\%$, $\delta t = 1$, $T = 4$

CU	l_v
1	40
2	46
3	57
4	82
5	22

CU	l_v
1	70
2	20
3	30
4	35
5	50

$t = 0$

$t = 1$

$t = 0$

$t = 1$

S1	S2	S3	S4
1	0	0	0
1	0	0	0
0	0	1	0
0	1	0	0
0	0	1	0

A_0

Numerical illustration
Server Capacity $= 100\%$, $\delta t = 1$, $T = 4$

CU	l_v
1	40
2	46
3	57
4	82
5	22

CU	l_v
1	70
2	20
3	30
4	35
5	50

$t = 0$ $t = 1$

$t = 0$ $t = 1$

1	0	0	0
1	0	0	0
0	0	1	0
0	1	0	0
0	0	1	0

1	0	0	0
1	0	0	0
0	0	1	0
0	1	0	0
0	0	1	0

A_0 $=$ A_1

$\rightarrow$ No Relocations

Numerical illustration
Server Capacity $= 100\%$, $\delta t = 1$, $T = 4$

CU	l_v
1	40
2	46
3	57
4	82
5	22

$t = 0$

CU	l_v
1	70
2	20
3	30
4	35
5	50

$t = 1$

CU	l_v
1	33
2	70
3	67
4	45
5	62

$\}> 100\%$

$> 100\%$

$t = 2$

$t = 0$

$t = 1$

$\rightarrow$ Need 2 Relocations, with 1 more server.

$\rightarrow$ Assume ρ_i's are same, relocate one with low $cost_{vm}$ ($\rightarrow l_v$)

1	0	0	0
1	0	0	0
0	0	1	0
0	1	0	0
0	0	1	0

A_0

1	0	0	0
1	0	0	0
0	0	1	0
0	1	0	0
0	0	1	0

A_1

Numerical illustration
Server Capacity $= 100\%$, $\delta t = 1$, $T = 4$

CU	l_v
1	40
2	46
3	57
4	82
5	22

$t = 0$

CU	l_v
1	70
2	20
3	30
4	35
5	50

$t = 1$

CU	l_v
1	33
2	70
3	67
4	45
5	62

$t = 2$

$t = 0$ $t = 1$ $t = 2$

S1   S2   S3   S4

1	0	0	0
1	0	0	0
0	0	1	0
0	1	0	0
0	0	1	0

A_0

1	0	0	0
1	0	0	0
0	0	1	0
0	1	0	0
0	0	1	0

A_1

Numerical illustration
Server Capacity $= 100\%$, $\delta t = 1$, $T = 4$

CU	l_v
1	40
2	46
3	57
4	82
5	22

CU	l_v
1	70
2	20
3	30
4	35
5	50

CU	l_v
1	33	✓
2	70	
3	67	
4	45	
5	62	✓

$t = 0$ $t = 1$ $t = 2$

$t = 0$ $t = 1$ $t = 2$

A_0

1	0	0	0
1	0	0	0
0	0	1	0
0	1	0	0
0	0	1	0

A_1

1	0	0	0
1	0	0	0
0	0	1	0
0	1	0	0
0	0	1	0

A_2

0	0	0	1
1	0	0	0
0	0	1	0
0	1	0	0
0	0	0	1

Numerical illustration
Server Capacity $= 100\%$, $\delta t = 1$, $T = 4$

CU	l_v
1	40
2	46
3	57
4	82
5	22

$t = 0$

CU	l_v
1	70
2	20
3	30
4	35
5	50

$t = 1$

CU	l_v
1	33
2	70
3	67
4	45
5	62

$t = 2$

CU	l_v
1	60
2	30
3	27
4	25
5	32

} $< 100\%$

$t = 3$

$t = 0$ $t = 1$ $t = 2$

→ chance for Consolidation, saves 2 servers

→ Relocate ones with low lv s

1	0	0	0
1	0	0	0
0	0	1	0
0	1	0	0
0	0	1	0

A_0

1	0	0	0
1	0	0	0
0	0	1	0
0	1	0	0
0	0	1	0

A_1

0	0	0	**1**
1	0	0	0
0	0	1	0
0	1	0	0
0	0	0	**1**

A_2

Numerical illustration
Server Capacity $= 100\%$, $\delta t = 1$, $T = 4$

CU	l_v
1	40
2	46
3	57
4	82
5	22

CU	l_v
1	70
2	20
3	30
4	35
5	50

CU	l_v
1	33
2	70
3	67
4	45
5	62

CU	l_v
1	60
2	30
3	27
4	25
5	32

$t = 0$ $t = 1$ $t = 2$ $t = 3$

$t = 0$ $t = 1$ $t = 2$ $t = 3$

1	0	0	0
1	0	0	0
0	0	1	0
0	1	0	0
0	0	1	0

1	0	0	0
1	0	0	0
0	0	1	0
0	1	0	0
0	0	1	0

0	0	0	1
1	0	0	0
0	0	1	0
0	1	0	0
0	0	0	1

A_0 A_1 A_2

Numerical illustration
Server Capacity $= 100\%$, $\delta t = 1$, $T = 4$

CU	l_v
1	40
2	46
3	57
4	82
5	22

CU	l_v
1	70
2	20
3	30
4	35
5	50

CU	l_v
1	33
2	70
3	67
4	45
5	62

CU	l_v
1	60
2	30
3	27
4	25
5	32

$t = 0$ $\qquad$ $t = 1$ $\qquad$ $t = 2$ $\qquad$ $t = 3$

$t = 0$ $\qquad$ $t = 1$ $\qquad$ $t = 2$ $\qquad$ $t = 3$

1	0	0	0
1	0	0	0
0	0	1	0
0	1	0	0
0	0	1	0

A_0

1	0	0	0
1	0	0	0
0	0	1	0
0	1	0	0
0	0	1	0

A_1

0	0	0	1
1	0	0	0
0	0	1	0
0	1	0	0
0	0	0	1

A_2

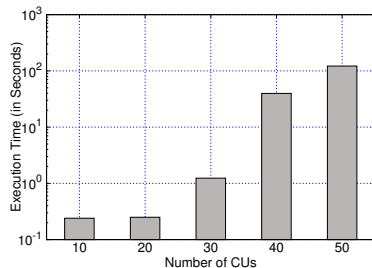| 0	0	0	1
1	0	0	0
1	0	0	0
1	0	0	0
0	0	0	1

A_3

ILP Execution Time

- Input size from 10 to 50 CUs
- Maximum execution time taken by the ILP model over 240 iterations
- 122 seconds ($\sim$ 2 minutes) to converge to the solution for 50 CUs.

Heuristics?

To alleviate the computational heaviness for larger input size, we can look forward to time-efficient heuristics approaches that produces solutions close to the optimal with acceptable service guarantees.

Relocation-Aware Heuristic Algorithm for KORA

Three distinct stages for every **overloaded** compute server.

1. **Candidate CU Selection :** Selecting a suitable candidate CU for relocation from an overloaded compute server (identified as source server). We adopt a Minimum Relocation Cost (MRC) policy, i.e., relocating a CU $v \in \mathcal{V}$, that has lowest relocation score (ζ_v). The relocation score metric ζ_v is calculated for each CU $v \in \mathcal{V}$ and is a weighted average of ws_v and lv.

$$\zeta_v = (\alpha \times ws_v) + ((1-\alpha) \times l_v), \text{ such that } 0 \leq \alpha \leq 1 \qquad (10)$$

2. **Determining Target Server :** Determining a non-overloaded, active target server to place chosen candidate CU. If no such server found, instantiate a new server as a target for candidate CU. We use a variant of Best Fit (BF) bin packing approximation algorithm to identify a target for candidate CU. Instantiates a new compute server in case there are no existing non-overloaded compute server to accommodate candidate CU.

3. **Perform CU relocation :** Iteratively write the active memory pages/contexts of candidate CU from source to target compute server. (live migration)

Proposed Heuristic Algorithm

- Relocation of CUs from **overloaded** compute servers.
- Consolidation of CUs in **underloaded** compute servers.

Algorithm 1 : Relocation-aware Greedy Heuristic for KORA

Input : Previous allocation matrix A_{t-1} and l_v for all CUs.
Output : Best possible allocation matrix A_t at time epoch t.

1: **procedure** GETALLOCATIONMATRIX
2:     **while** (S_o is not $NULL$) **do**
3:         $excess \leftarrow \left(\sum_{A_t(v)=m}(l_v) \right) - C_m$
4:         Find eligible CUs for relocation *i.e.,* $l_v > excess$
5:         Compute ζ_v for all eligible CUs
6:         $CandidateCU \leftarrow$ CU with lowest ζ_v
7:         Select a target compute server β for $CandidateCU$
8:         **if** $\exists \beta$ **then**
9:             Relocate $CandidateCU$ to β
10:        **else**
11:            Instantiate a new compute server β' as target
12:            Relocate $CandidateCU$ to β'
13:        **end if**
14:        Update S_o and S_n
15:    **end while**
16:    **while** (S_u is not $NULL$) **do**
17:        Merge elements of S_u respecting capacity constraint
18:    **end while**
19:    Return the new allocation matrix A_t
20: **end procedure**

Simulation Parameters

Parameter	Value
Network Area	10 KM $\times$ 10 KM
Number of RRUs	100
Users	1000
Tx Power of RRU	1 Watt
Sampling Interval	6 Minutes
Total Traffic Capture Window	24 Hours
Total Generated Samples	240
RRU workload Range	Normalized in [0,1]
Peak CU Compute Load	100%
$[w_1, w_2, w_3, w_4, w_5]$	$[0.10, 0.30, 0.20, 0.25, 0.15]$
Traffic generation process	Gaussian Mixture Model

Results .. 1

Figure: Total Number of Affected GBR Flows
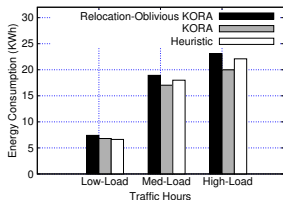
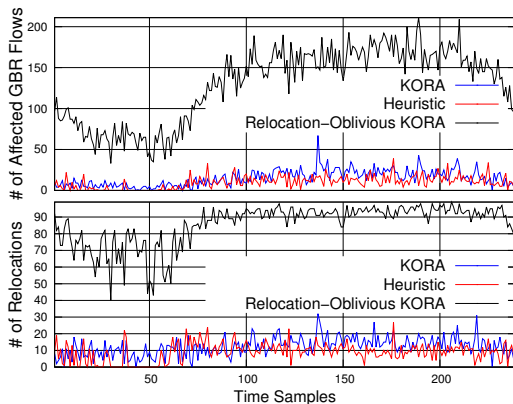**Figure:** Total Number of CU Relocations.
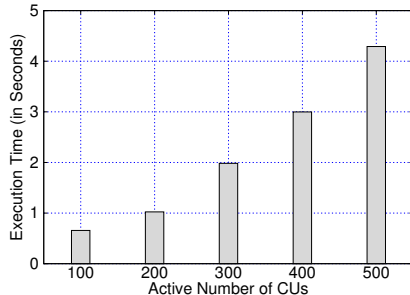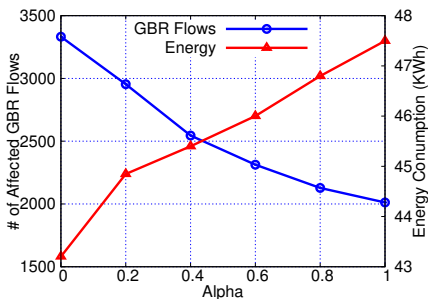
Figure: Total Energy Consumption (KWh).

- *Relocation-Oblivious* KORA only focuses on minimizing the total energy consumption due to active compute servers and does not factor the relocation cost. Therefore, it incurs disruption to a large number of GBR flows (~ 13296 in High_Load) in all the three traffic scenarios.

- KORA is able to outperform *relocation-oblivious* scheme by saving 88.53% of affected GBR flows.

- The number of active relocations incurred are 85.74% less than that of relocation occurred with *relocation-oblivious* scheme.

Results .. 2

- Linearly Proportional relationship between number of GBR flows affected and number of relocations occurring at any time epoch.
- A rise in relocation count also impacts the flow disruption proportionally.

Results .. 3

- By controlling α value appropriately, the service provider can optimally choose a suitable policy for their users.

- At $\alpha = 1$, the heuristic algorithm is able to save 39.62% of affected GBR flows than that of $\alpha = 0$, but the energy consumption is increased by 7.45%. We considered $\alpha = 0.43$, where two contrasting objectives are equally good.

- In contrast to the execution time of ILP model, heuristic is light-weight and executes in order of few seconds.

Conclusions

- Different trade-offs involved in dynamic consolidation and relocation of CUs in C-RAN is studied in a novel and efficient resource management framework, KORA.

Conclusions

- Different trade-offs involved in dynamic consolidation and relocation of CUs in C-RAN is studied in a novel and efficient resource management framework, KORA.

- First, we formulated the problem as an ILP optimization model and then characterized the optimal solution w.r.t. *relocation-oblivious* and *relocation-aware* objectives.

Conclusions

- Different trade-offs involved in dynamic consolidation and relocation of CUs in C-RAN is studied in a novel and efficient resource management framework, KORA.

- First, we formulated the problem as an ILP optimization model and then characterized the optimal solution w.r.t. *relocation-oblivious* and *relocation-aware* objectives.

- A scalable, time-efficient relocation-aware heuristic algorithm is proposed.

Conclusions

- Different trade-offs involved in dynamic consolidation and relocation of CUs in C-RAN is studied in a novel and efficient resource management framework, KORA.

- First, we formulated the problem as an ILP optimization model and then characterized the optimal solution w.r.t. *relocation-oblivious* and *relocation-aware* objectives.

- A scalable, time-efficient relocation-aware heuristic algorithm is proposed.

- The proposed heuristic algorithm saves 27% of relocations and 33% of GBR flows from disruption, but consumes 6.6% more energy than KORA.

Conclusions

- Different trade-offs involved in dynamic consolidation and relocation of CUs in C-RAN is studied in a novel and efficient resource management framework, KORA.

- First, we formulated the problem as an ILP optimization model and then characterized the optimal solution w.r.t. *relocation-oblivious* and *relocation-aware* objectives.

- A scalable, time-efficient relocation-aware heuristic algorithm is proposed.

- The proposed heuristic algorithm saves 27% of relocations and 33% of GBR flows from disruption, but consumes 6.6% more energy than KORA.

- **Future work**: prototyping C-RAN system using OAI for different split options and factoring split-specific constraints in optimization models.

Acknowledgements

References I

China Mobile, *C-RAN - The road towards green RAN,,   ,China Mobile White Paper*, 2011.

Manli Qian and Wibowo Hardjawana and Jinglin Shi, and Branka Vucetice, *Baseband Processing Units Virtualization for Cloud Radio Access Networks,   ,IEEE WIRELESS COMMUNICATIONS LETTERS, VOL. 4, NO. 2, APRIL 2015*

Sourjya Bhaumik et al, *CloudIQ: A Framework for Processing Base Stations in a Data Center,   ,IEEE Mobicom, 2012*

Nikaein, Navid, *"Processing Radio Access Network Functions in the Cloud: Critical Issues and Modeling", Proceedings of the 6th International Workshop on Mobile Cloud Computing and Services, 3643*, 2004

White paper, *"Cisco Visual Networking Index, Global mobile data traffic forecast update, 2013–2018", Online*, 2014.

Hong Xu and Baochun Li *Anchor: A Versatile and Efficient Framework for Resource Management in the Cloud,   ,IEEE TRANSACTIONS ON PARALLEL AND DISTRIBUTED SYSTEMS,VOL. 24,NO. 6,JUNE 2013*

Gale, David, and Lloyd S. Shapley. *College admissions and the stability of marriage,   ,The American Mathematical Monthly 69.1 (1962): 9-15.*

Navid Nikaein et al. *Demo: Closer to Cloud-RAN: RAN as a Service,   ,International Conference on Mobile Computing and Networking, Mobicom 2015, Pages 193-195*

THANK YOU

QUERIES ?