Algorithm 1: Proposed algorithm to exhaustively evaluate operating states within the prediction horizon T.

Input: b_{iu_k}, T, $x(t)$
Output: $\hat{u}(t)$, $\hat{x}(t)$

Initialize all inputs: $\mathcal{S}_t = x(t)$, $J(x(t)) = 0$
For $t = 1 : T$ **do**
  Predict environment parameters for $t + 1$
  $s_{t+1} \neq \emptyset$
  For $x \in \mathcal{S}_t$ **do**
    For $u \in U$ **do**
      Estimate state for $t + 1$, $\hat{x} = \phi(x, u)$
      $J(\hat{x}) = \min_{u(.)} J(x(t), u(.))$
      $\mathcal{S}_{t+1} = \mathcal{S}_{t+1} \cup \{\hat{x}\}$
    End For
  End For
  $t = t + 1$
Find $x_{min} \in \mathcal{S}_T$ with minimum cost $J(x)$
$\hat{u}(t)$ = initial input leading from $x(t)$ to x_{min}
Return $\hat{u}(t)$, $\hat{x}(t)$

accumulated cost, plus the cost associated with the current time step $t+n$. When this exploration has finished, the action at time t that leads to the best final accumulated cost, at time $t+T$, is selected at the optimal operating value.

V. Simulation Results and Discussion

Using the state vector, the SAE is trained for the QoS and energy saving using traffic flow as an input data set obtained from a traffic flow simulator obtained from [24]. The data set is aggregated into time-slots $t = 1$ second and arrival patterns are extracted. The data set is then split into 30% for training and 70% for testing. To validate our main findings, we show some selected numerical results where we consider a cell radius of 300 meters, carrier frequency of 2.1GHz and a system bandwidth of 8MHz (South African standard for CRs), the number of RBs is 100. P_{tx} is 46dBm [40W], P_{on} is 40.25dBm [10.6W], P_{idle} is 50dBm [100W], and P_{server} is 56.74dBm [472.3W].

Fig. 2, presents a resource allocation performance comparison between two variants of dynamic resource percentage threshold (varied with GP alone, GP + Bipartite). Here, it can be observed that the achievable capacity for SUs decreases, but by combining dynamic resource percentage threshold with bipartite matching achieves better performance through the GP solution.

Table I presents root mean square error (RMSE) convergence performance of the training and validation process of the SAE. The SAE was trained using 110 epochs, each epoch consisting of 2,000 individual training trials, with a batch size of 1. As seen from Table Is, a better performance loss of 0.10 (i.e., 10%) is obtained, which is a good performance considering the size of the data. Fig. 3 shows the BS load pattern prediction results based on the SAE DNN architecture for a time horizon of $T = 90$ seconds. Throughout the prediction horizon, there is an upward and downward trend and no obvious seasonality can be observed. This is because the data was aggregated into shorter time scales in order to exposed the microscopic behavior of modern day network

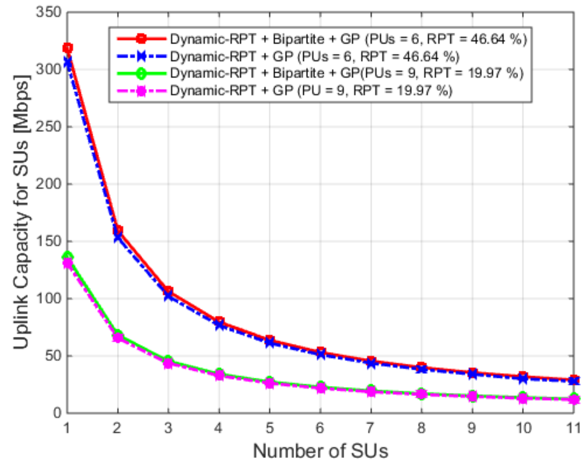

Fig. 2: UL achievable capacity per SU.

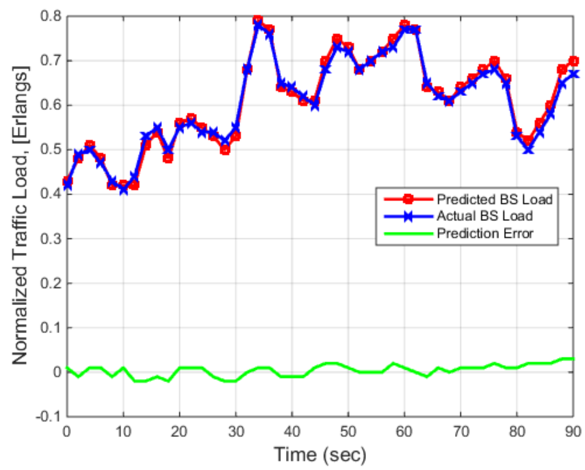

Fig. 3: BS load prediction using an SAE DNN architecture.

traffic. Fig. 4 shows the evolution of the mean energy saving with respect to the optimization weight α. A drop in the energy saving is observed when $\alpha \geq 0.5$, i.e., as $\alpha \rightarrow 1$, the QoS is prioritized over BS energy consumption. The exploration technique performs 9% better than the random tree in saving energy even when provision priority shift to QoS at $\alpha \geq 0.5$.

VI. Conclusion

This paper envisioned a computational-resource-aware energy consumption technique using deep learning. The predicted future behavior of QoS requirements is optimized by selecting the best control actions to apply to the system in the trade-off between QoS and energy saving. An exploration technique is proposed to perform the trade-off between energy saving and QoS. The simulation results show that the proposed exploration technique performs 9% better than the traditional random tree technique even when the provisioning priority shifts away from energy saving towards QoS, i.e., $\alpha \geq 0.5$. This shows that

Stacked Autoencoder (SAE)											
Training Epoch	10	20	30	40	50	60	70	80	90	100	110
Training Loss	0.3115	0.2819	0.2284	0.1711	0.1493	0.1185	0.1110	0.1084	0.1065	0.1000	0.1000
Validation Loss	0.2805	0.2529	0.2054	0.1505	0.1399	0.1176	0.1109	0.1082	0.1065	0.1000	0.1000

TABLE I: This table shows the training and validation results for the MLP SAE DNN.

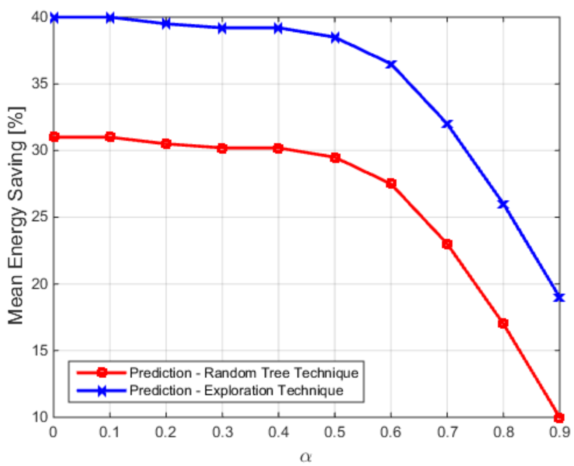

Fig. 4: Mean energy saving as a function of α.

the adoption of predictive analytics can be useful in providing energy efficiency solutions.

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