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Design of a Hybrid Bio-inspired Model for Improving Addressing Capabilities of IPv6 Networks

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Abstract

Addressing in IPv6 networks is a complex task, that involves multiple decision criterion that include base addressing, subnet addressing, location & energy aware addressing, and temporal performance aware addressing constraints. To incorporate these constraints a wide variety of models are proposed by researchers, and most them utilize location-aware addressing and do not consider multimodal parameters. Schemes that consider these parameters are either highly complex, or cannot be scaled for heterogeneous network scenarios. To overcome these limitations, this text proposes design of a novel hybrid bioinspired model that assists in improving addressing capabilities of IPv6 networks. The proposed model bee colony optimization (BCO), genetic algorithm (GA), and particle swarm optimization (PSO) in order to improve addressing quality for different network types. Initially, GA is used to stochastically assign location-specific addresses to a simulated network, which is incrementally tuned by PSO via a cognitive & social learning process. The fine-tuned addresses are further optimized via integration of BCO model, which assists in integrating energy awareness. Final addresses are initially simulated with exhaustive communication test, and then deployed to real-time networks for optimized operations. Due to which, the assigned addresses are observed to be delay & energy efficient, thereby assisting in deploying them for real-time use cases. The proposed addressing model was tested under different scaled networks, and an energy efficiency of 8.3%, with delay reduction of 6.5% was achieved when compared with various state-of-the-art methods, which assists in deploying the model for multiple scaled network scenarios.

Keywords: Addressing, BCO, Bioinspired, Cognitive, Delay, Stochastic GA, Hybrid, IPv6, PSO, Social, Energy.

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Introduction

IPv6 network address assignment is a multi-domain task that includes the development of location-aware address evaluation, as well as ongoing network monitoring and performance optimization. In this process, routing prefix-based addresses are first assigned to core routers for subnetting, and then region-based router nodes extend those addresses to include client nodes' interface identifiers (IDs). This 3-step addressing scheme makes it easier for routers to identify nearby nodes for low-power and high-speed routing performance. Routing prefixes must be assigned to nodes that are closer in proximity in order to design such addressing schemes. Similarly, subnet addresses must be assigned in order to facilitate the identification of nearby access nodes during the routing process.[1] Some researchers use these operations as a foundation for various addressing models that have varying degrees of computational latency, energy efficiency and applicability. IPv6 addressing has multiple applications, for instance, it can be applied on the internet control message protocol (ICMP), which uses communication between a PC node and a router via switching devices.

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IPv6 header and ICMPv6 header are first defined by a PC in the model, which is then passed through a switching device for communication checks. IPv6 subnet address identification, routing address extraction, and network ID evaluation are all part of these checks. The router uses these IDs to verify packets, which allows it to allow or deny different communication requests. Next section discusses similar models,[2-4] as well as their network specific nuances; application-specific advantages; functional limitations; and contextual future research scopes. Following the discussion, it was found that majority of these models use a static addressing method, which limits their ability to scale to large networks of any size or complexity. Dynamic addressing models are extremely difficult to implement, resulting in lower QoS for large networks. It was further observed that most these utilize location-aware addressing, and do not consider multimodal parameters. Schemes that consider these parameters are either highly complex, or cannot be scaled for heterogeneous network scenarios. To overcome these limitations, section 3 proposes design of a novel hybrid bioinspired model that assists in improving addressing capabilities of IPv6 networks. The model was tested under multiple network scenarios, and its performance was compared w.r.t. other models in terms of communication delay and energy consumption parameters. This text concludes with some network-specific observations about the proposed model, and also recommends methods to further optimize it performance under multiple use case scenarios.

Background and Related Work

For IPv6 addressing, researchers have proposed a huge variety of distinct models, each of which is distinct from the others in terms of the internal performance characteristics it provides. For instance, the research that is presented in[5,6], suggests the utilization of transition measurements, static context header compression (SCHC), which enables networks to assign low latency addresses but cannot be scaled for overall quality of service optimizations. [Citation needed] Survival analysis and prediction model (SAPM) is a model that integrates location awareness along with other quality of service metrics such as packet delivery ratio, throughput, and energy consumption levels. This is accomplished by combining autonomous systems with the parameters of internet service providers. In the work,[7] a potential solution to the issue of scalability is presented in the form of this model. The following references discuss models that are comparable to these.[8-10] These models propose the use of lookups with prefix characteristics (LPC), which helps to incorporate security during the process of address assignment. They also propose security enabled network designs and conditional privacy preservation with mutual authentication, both of which help to protect users' privacy. These models are further extended in,[11-13] in which memory efficient hash-based longest prefix matching model (MEHLPM) and IP network diversity are used for the purpose of improving the performance of large-scale networks under scenarios involving heterogeneous nodes. Another model that is put into practice is known as dual-stack network management.

Models that utilize identity-based cryptography,[14] DNS hierarchies,[15] time-slotted channel hopping (TSCH),[16] network-aware internet-wide scan,[17] privacy-preserving communication schemes,[18] non-batch verification method scheme (NBVMS),[19] and efficient, secure, and privacy-preserving proxy mobile IPv6 (ESP-PMIPv6)[20] are also discussed; these models help optimize security along with quality of service while These models, which have a high level of complexity, are not suitable for use in network configurations that call for simplified addressing schemes because of the level of complexity they possess. The research presented in[21-23] suggests the use of low-power lossy networks, fast handovers for mobile IPv6 (FMIPv6), and block chains. The purpose of these three methods is to maximize addressing speed while simultaneously reducing QoS performance in large-scale scenarios. This is an attempt to assist in finding a solution to the issue that has been recognized. This performance is improved in,[24-26] which describes the use of edge-based software-defined network (ESDN) next hop-selectable forwarding information base (NSFIB), as well as SDN models, for highly efficient addressing, along with improved QoS levels.[24-26] are all references to the same article.[24] These models have been expanded in[27-29] to include evolutionary software defined networking, online quantitative security analysis, and end-to-end TCP congestion control in order to manage large-scale network traffic scenarios. This expansion was done for the purpose of managing large-scale network traffic scenarios. Both[30] and[31] discuss models that are very similar to one another. In both of these articles, the authors propose using time to reside (TTR) in conjunction with a distributed multi-agent framework in order to increase the network's resilience to mobility aware traffic. The scalability of these models, as well as the performance levels of their deployments, are severely constrained, however, because of the extreme complexity of the models. In the section that follows, an idea is presented for the creation of a novel hybrid bioinspired model with the purpose of enhancing the addressing capabilities of IPv6 networks in order to solve the problems that have been identified. The proposed addressing model was also evaluated in terms of a number of different quality-of-service metrics, and it was compared to a number of different state-of-the-art methods while being tested with multiple different node variation scenarios.

Proposed Design of A Novel Hybrid Bioinspired Model for Improving Addressing Capabilities of Ipv6 Networks

After referring the literature review, it can be observed that existing addressing models do not take into account multimodal parameters and use singular parameter-aware addressing, which might be sufficient for small-scale networks. But the complexity of these schemes prevents them from being scaled for heterogeneous network scenarios. This section discusses design of a novel hybrid bioinspired model to help IPv6 networks improve their addressing capabilities in order to get around these drawbacks. To enhance addressing quality for various network types, the proposed model uses bee colony optimization (BCO), genetic algorithm (GA), and particle swarm optimization (PSO), which can be observed from Figure 1, wherein overall flow of the proposed model is visualized under different network use cases.

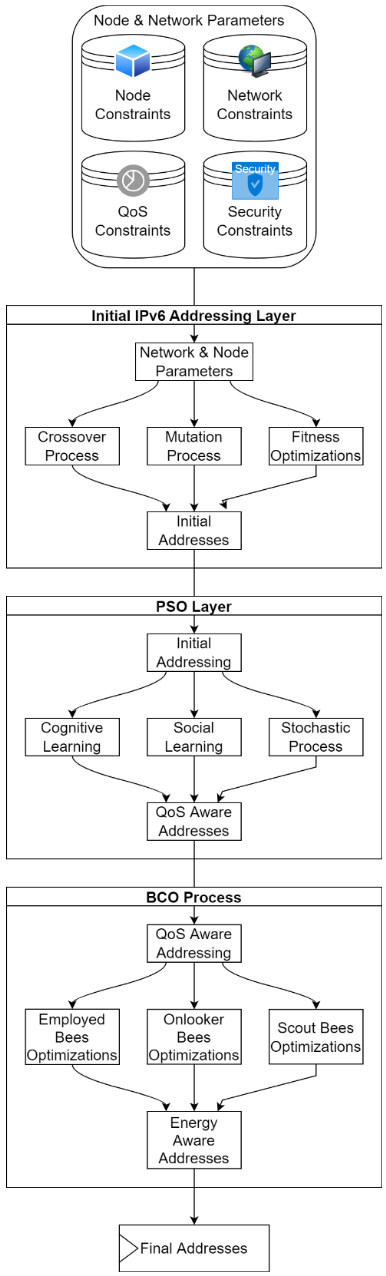

Figure 1: Overall Flow of the proposed addressing scheme

Initial location-specific addresses are stochastically assigned to a simulated network using GA, which are then incrementally tuned by PSO using a cognitive & social learning process. Incorporation of the BCO model, aids in integrating energy awareness, due to which the fine-tuned addressing scheme is further optimized. In order to ensure optimal performance, final addresses are first deployed to real-time networks after extensive communication-level simulations. As a result, it has been observed that the assigned addresses are delay-aware and energy-efficient, making it easier to deploy for real-time use cases.

Thus, initially a GA Model is used for location-aware addressing, which works via the following process.

To initialize the GA Model, following parameters are setup, and all solutions are marked as 'mutate'

- Total optimization solutions (Ns) - total number of optimal solutions
- Total optimization iterations (Ni) - total number of optimal iterations
- Rate at which the model will learn (Nr)- rate at which the model will produce the output
- Extent of network size (Nz)- total size of the network
- Maximum energy of each node ()- energy level of node
- Transmission & Reception energy levels () - energy level of node during transmission and reception of data.

Iterate the following process times, and while scanning each solution,

- If solution has been marked as 'mutate', then reconfigure its addressing, else skip it and go to next solutions
- For reconfiguration, assign a stochastic Interface ID in the form of Base Address, Sub Net Address, and Device Address, while maintaining a fixed Site Prefix and Subnet ID
- Based on this address, modify node locations, evaluate solution fitness via equation 1,

Where, represents number of nodes, while represents node positions.

- Evaluate such fitness levels for each solution, and at the end of each iteration calculate iteration fitness threshold via equation 2,
- Once an iteration is completed, change solution status to 'crossover' if , else keep its status as 'mutate', and reconfigure it in the consecutive iterations

Solutions from the final iteration are processed via a PSO model, which assists in incorporating temporal throughput and packet delivery ratio parameters during address assignments. This model works via the following process,

- Setup particle best fitness for all solutions via equation 3, where, represents packet delivery ratio and throughput for previous communications.
- Mark solution with lowest fitness as global best via equation 4,
- Scan each iteration, and modify solution velocity via equation 5,

Where, represents stochastic numbers in the range (0,1), while represents cognitive and social learning rates, which can be setup by the designers to achieve optimum addressing performance levels.

- Solution fitness is updated if, else it is kept unchanged in consecutive iterations.
- Global best fitness levels are updated after each iteration for optimum performance levels.
- At the end of each iteration, addressing is modified by the GA model, and its fitness is used for generation of new particle positions.

Based on this process, the addressing scheme is able to incorporate throughput and PDR levels. This scheme is further extended by a BCO Model, which works via the following process:

- Iterate times, and for each iteration, identify 2 Onlooker Bees via equation 6,

Where, represents a stochastic Markovian process that generates numbers between the range sets.

- Fitness levels for each of these bees is evaluated via equation 7,

Where, represents fitness obtained via the PSO Model, while represents fitness levels of selected onlooker bees.

- The bee is selected upgraded to 'Employed Bee', if it has a higher fitness, else it is marked as 'Scout Bee'
- This process is repeated for iterations

At the end of all iterations, all 'Employed Bees' are scanned, and bees with lowest fitness levels are selected for address assignments. This process is repeated for every new node that joins the network, which assists in assignment of low delay, low energy, high PDR and high throughput addresses. To validate the performance of this model, these parameters are compared with existing state-of-the-art addressing schemes in the next section of this text.

Result

The proposed model uses a combination of GA with PSO & BCO for incorporating delay-awareness, energy-awareness, throughput-awareness and PDR-awareness, which assists in efficient addressing in different IPv6 networks. To evaluate its performance, the proposed model was compared with standard addressing models which are SCHC,[6] LPC,[8] and ESDN.[24] These networks are examined using various network scenarios and networking situations. The number of nodes (NN) was varied linearly between 500 and 20,000 using normal network and node design, and the same nodes were picked for routing purposes. The average QoS metrics for energy consumption (E), end-to-end communication delay (D), packet delivery ratio (PDR), and throughput (T) were examined during node communications. According to this assessment procedure, the end-to-end delay (D) values for several procedures are given in Table 1.

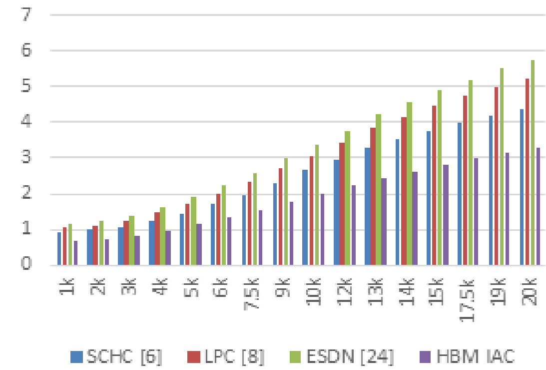

Figure 2: End-to-End Delay v/s Number of Nodes for different addressing models

Based on this evaluation and Figure 2, it can be observed that the proposed model showcases 15.5% lower delay when compared with SCHC,[6] 25.4% lower delay when compared with LPC,[8] and 28.9% lower delay when compared with ESDN,[24] which makes it useful for high-speed applications. This is due to incorporation of node-to-node distance in GA Model while performing address assignments. Similar

Table 1: Average end-to-end delay for different addressing models

NN	*D (ms) SCHC [6]*	*D (ms) LPC [8]*	*D (ms) ESDN [24]*	*D (ms) HBMIAC*
1k	0.93	1.05	1.14	0.67
2k	0.99	1.12	1.24	0.74
3k	1.07	1.25	1.40	0.84
4k	1.23	1.46	1.64	0.98
5k	1.45	1.72	1.92	1.14
6k	1.70	2.00	2.22	1.33
7.5k	1.96	2.32	2.58	1.54
9k	2.29	2.70	2.98	1.77
10k	2.65	3.06	3.37	2.00
12k	2.97	3.43	3.77	2.22
13k	3.27	3.84	4.21	2.45
14k	3.52	4.16	4.56	2.64
15k	3.77	4.46	4.89	2.83
17.5k	3.99	4.74	5.20	3.00
19k	4.19	5.00	5.49	3.15
20k	4.38	5.22	5.73	3.30

Table 2: Average energy consumption for different addressing models

NN	*E (mJ) SCHC [6]*	*E (mJ) LPC [8]*	*E (mJ) ESDN [24]*	*E (mJ) Proposed*
1k	2.32	3.50	3.10	1.86
2k	2.50	3.72	3.28	1.97
3k	2.62	3.90	3.44	2.07
4k	2.75	4.09	3.60	2.16
5k	2.87	4.28	3.77	2.27
6k	3.01	4.50	3.97	2.39
7.5k	3.18	4.74	4.17	2.51
9k	3.35	4.96	4.36	2.62
10k	3.52	5.20	4.56	2.74
12k	3.70	5.44	4.76	2.86
13k	3.88	5.68	4.96	2.97
14k	4.06	5.89	5.13	3.07
15k	4.20	6.08	5.30	3.17
17.5k	4.33	6.29	5.48	3.28
19k	4.49	6.51	5.67	3.39
20k	4.64	6.72	5.85	3.50

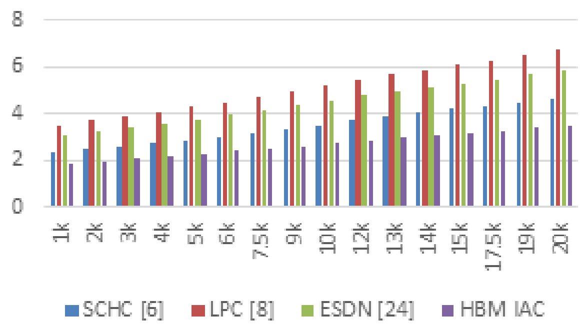

Figure 3: Energy consumption v/s number of nodes for different addressing models

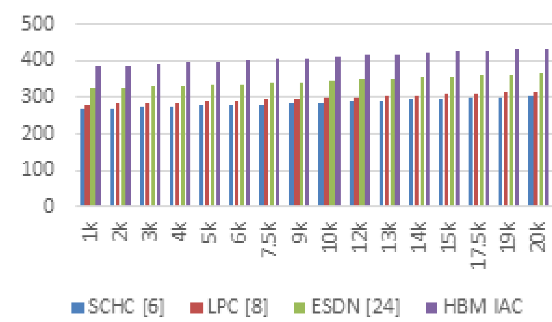

Figure 4: Throughput v/s number of nodes for different addressing models

observations are done for energy performance, this can be observed from table II as follows,

Based on this evaluation and Figure 3, it can be observed that the proposed model showcases 8.3% lower energy consumption when compared with SCHC,[6] 9.5% lower energy consumption when compared with LPC,[8] and 8.5% lower energy consumption when compared with ESDN,[24] which makes it useful for high network lifetime applications.

This is due to incorporation of energy levels in BCO Model while performing address assignments. Similar observations are done for throughput performance, and can be observed from table III as follows.

Based on this evaluation and figure 4, it can be observed that the proposed model showcases 19.5% higher throughput when compared with SCHC,[6] 18.3% higher throughput when compared with LPC,[8] and 15.4% higher throughput when compared with ESDN,[24] which makes it useful for high-speed application scenarios. This is due to incorporation of temporal throughput in PSO Model while performing address assignments. Similar observations are done for packet delivery rate (P) performance, and can be observed from table IV as follows.

Based on this evaluation and figure 5, it can be observed that the proposed model showcases 10.5% higher PDR when compared with SCHC,[6] 12.4% higher PDR when compared with LPC,[8] and 9.5% higher PDR when compared with ESDN,[24] which makes it useful for low packet error application scenarios.

This is due to incorporation of temporal PDR in PSO Model while performing address assignments. Thus, when

Table 3: Average throughput performance for different addressing models

NN	*T (kbps) SCHC*[6]	*T (kbps) LPC*[8]	*T (kbps) ESDN*[24]	*T (kbps) Proposed*
1k	267.88	279.50	323.24	385.19
2k	270.14	281.79	325.90	388.37
3k	272.27	284.11	328.62	391.63
4k	274.61	286.54	331.44	394.97
5k	276.97	288.95	334.24	398.27
6k	279.27	291.33	337.01	401.55
7.5k	281.57	293.71	339.78	404.82
9k	283.87	296.11	342.53	408.10
10k	286.17	298.51	345.28	411.37
12k	288.47	300.90	348.02	414.64
13k	290.76	303.28	350.76	417.90
14k	293.05	305.65	353.49	421.16
15k	295.33	308.02	356.23	424.42
17.5k	297.61	310.38	358.97	427.68
19k	299.88	312.73	361.71	430.94
20k	302.16	315.09	364.45	434.20

Table 4: Average packet delivery ratio performance for different addressing

NN	*PDR (%) SCHC*[6]	*PDR (%) LPC*[8]	*PDR (%) ESDN*[24]	*PDR (%) Proposed*
1k	78.33	77.97	78.85	88.03
2k	78.99	78.60	79.49	88.75
3k	79.61	79.25	80.15	89.50
4k	80.29	79.93	80.84	90.26
5k	80.98	80.61	81.52	91.02
6k	81.65	81.27	82.19	91.77
7.5k	82.33	81.94	82.86	92.52
9k	83.00	82.61	83.54	93.27
10k	83.67	83.27	84.21	94.02
12k	84.34	83.94	84.88	94.77
13k	85.02	84.61	85.55	95.52
14k	85.68	85.27	86.22	96.27
15k	86.35	85.93	86.89	97.01
17.5k	87.02	86.59	87.56	97.76
19k	87.68	87.25	88.22	98.51
20k	88.35	87.91	88.89	99.25

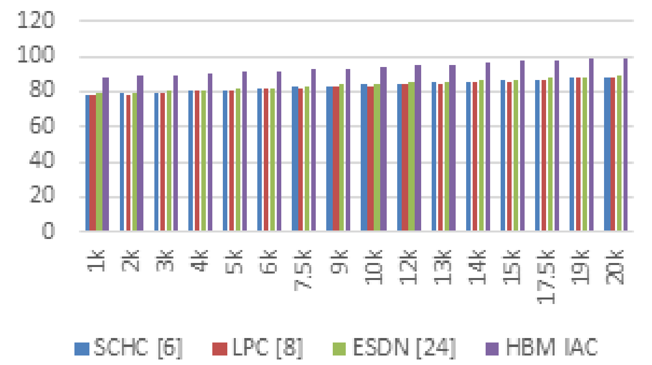

Figure 5: PDR v/s Number of Nodes for different addressing models

compared to other conventional models, it is clear that the model that was suggested is much superior in terms of end-to-end latency, communication throughput, energy efficiency, and packet delivery ratio measures, thereby making it highly applicable for multiple scaled IPv6 network scenarios.

Conclusion

The proposed model is able to fuse 3 highly optimized bioinspired computing methods, and extract highly efficient addresses based on their instantaneous and temporal performance levels. The GA Model is suited for single parameter optimizations; thus, it is used to optimize node-to-node communication delays while address assignments. While, PSO is suited multiple objective optimizations for throughput and PDR parameters. These models are integrated with a BCO Model, which assists in incorporating energy efficiency during addressing operations. The proposed addressing method can achieve 15.5% lower delay compared to SCHC,[6] 25.4% lower delay compared to LPC,[8] and 28.9% lower delay compared to ESDN[24] thanks to the combination of these 3 models, making it useful for high-speed applications. This is because when performing address assignments, the GA Model incorporates node-to-node distance. Similar to how SCHC[6] consumes 8.3% less energy than LPC,[8] ESDN[24] consumes 9.5% less energy than LPC,[8] and [R4] consumes 8.5% less energy than ESDN,[24] the proposed model is advantageous for applications requiring long network lifetimes. This is because when performing address assignments, the BCO Model incorporates energy levels. Additionally, it was noted that the proposed model exhibits throughput gains of 19.5% when compared to SCHC,[6] 18.3% when compared to LPC,[8] and 15.4% when compared to ESDN,[24] making it useful for high-speed application scenarios. This is because address assignments in the PSO Model incorporate temporal throughput. The proposed model is advantageous for low packet error application scenarios because it exhibits 10.5% higher PDR when compared with SCHC,[6] 12.4% higher PDR when compared with LPC,[8] and 9.5% higher PDR when compared with ESDN [24] in terms of packet delivery performance. This is because address assignments in the PSO Model incorporate temporal PDR. In light of this, it is evident that the suggested model is vastly superior to other conventional models in terms of end-to-end latency, communication throughput, energy efficiency, and packet delivery ratio measures, making it highly applicable for a variety of scaled IPv6 network scenarios. Future research can incorporate additional bioinspired models, such as Grey Wolf Optimization (GWO), Elephant Herding Optimization (EHO), and others to further enhance network performance. In order to create parameter aware addressing models that function in a variety of scenarios, researchers can also integrate deep learning techniques like convolutional neural networks (CNNs), recurrent neural networks (RNNs), etc. which will assist in better addressing performance due to their highly efficient feature processing capabilities.

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