Cooperative Agent-based SANET Architecture for Personalised Healthcare Monitoring

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Abstract—**The application of an software agent-based computational technique that implements Extended Kohonen Maps (EKMs) for the management of Sensor-Actuator networks (SANETs) in health-care facilities. The agent-based model incorporates the BDI (Belief-Desire-Intention) Agent paradigms by Georgeff et al. EKMs perform the quantitative analysis of an algorithmic artificial neural network process by using an indirect-mapping EKM to self-organize. Current results show a combinatorial approach to optimization with EKMs provides an improvement in event trajectory estimation compared to standalone cooperative EKM processes to allow responsive event detection for patient monitoring scenarios. This will allow healthcare professionals to focus less on administrative tasks, and more on improving patient needs, particularly with people who are in need for dedicated care and round-the-clock monitoring.**

Keywords— **BDI Agent Framework, Extended Kohonen Maps (EKM), Healthcare Infrastructures, Sensor Actuator Networks (SANETs)**

I. Purpose of SANET Infrastructures

A distributed SANET infrastructure using biomimetic principles for active monitoring of patients in healthcare is an on-going concern for modern medical practice. Current health practice is overly dependent upon existing passive communication devices, such as pagers and buzzers that can potentially distract staff from their daily tasks. Furthermore, the priority of these notices must be made by the staff alone, as these systems do not have the capability to measure which patient requires the most attention, so there is a greater responsibility to ensure staff have ease of access to patient record data at a moment's notice. For these main reasons, an evolvable network that encapsulates monitoring and patient record processes for health care will augment existing practices by tracking the wellbeing of a patient into their recovery.

The design of a SANET-based infrastructure for healthcare needs to adhere to industry standards including HL7 [10], but also take into consideration the human-user interaction needs for the end user. From a technical standpoint, efficient and concise data exchange is an imperative need for actively tracking and monitoring changes in event, but also to ensure that a systemic infrastructure suitable for SANET environments [6][7] is compatible with health care professional needs for ensuring the well-being of their patients in care and rehabilitation.

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From a qualitative standpoint, the SANET infrastructure model must be designed with hard real-time criticality and fault-tolerance, while incorporating redundancy to ensure the data responses and feedback is delivered within finite limits. Thus, the infrastructure must achieve strict Quality of Service (QoS) qualitative requirements [3][21], inclusive of scalability, robustness, security, privacy and efficiency. The SANET infrastructure should support the process of software development by facilitating integration of components and reducing the accidental complexities related to heterogeneous environments in health institutions. The Cooperative-Oriented Sensors Actuators model (COSA) by Chaczko [5] is used to represent a SANET neighborhood and its moderation by two global aspects: the accuracy of a node's position and the node's immunity to error propagation.

The algorithmic categories that are considered in the experimental model are ordered from local to global domain concerns. These include the following concepts of feature mapping of sensory inputs (using neural network techniques), multi-variate regression to reduce sampling errors, and multi-objective heuristics to provide future learning capability into the system:

- **Feature Mapping:**
  Utilizing an Extended Kohonen Map (EKM) by Kohonen [17][18], the self-organizing map partitions sensory-aware spaces discretely; thus the generalization capability arises from its self-organization during map training [19]. Map resolution is improved in frequently encountered stimuli regions, thus mimicking biological sensory perceptions where reinforced practice allows for prediction of anticipated events.
- **Multi-variate Regression Techniques:**
  Formulated as a non-linear multi-variate regression problem [11][13][14], the main issue is that training samples must be regularly collected for error sampling rates. The sampling process is simplified by providing qualitative feedback at the end of the executing control sequence [14]. This technique ensures smoothness when local minima or maxima results are encountered, such that sensor variations are minimized.
- **Multi-Objective Meta-Heuristics:**
  Reinforcement learning heuristics, based upon non-deterministic biological concepts, provides a best effort optimum routing and clustering organization solution depending on the current situation [4]. The feedback loop is closed to ensure that knowledge from the environment is retained

A. Basis of BDI-based Agent Infrastructures for SANETs

The foundation of the experimental design is based on the Jadex, a Jade compliant agent development system designed by Universität Hamburg. Objected-oriented concepts form the basis of the BDI infrastructure, based on Java, a platform-agnostic programming language that allows implementation and execution on a Java-compatible runtime environment. The principles of BDI agencies is from the Foundation for Intelligent Physical Agents (FIPA), an organization created to standardize the development of artificially intelligent agents in software projects, of which Jadex is a category member [11].

The importance of the design of the middleware framework is from a utilitarian perspective; while the SANET agencies are designed in Jadex, the adherence to Jade compatibility standards ensures the framework can be easily ported to any Jade development environment [11]. As shown in Figure 1: Middleware Agencies in BDI Framework, the Multi-Agent System (MAS) middleware framework integrates the perceptions from the environmental space and transforms them into the agent space. The three core agencies in the framework consist of:

- Virtual agents are purely 'software' agents that emulates the behavior of a desired agent artifact for experimental practice, such as a sensor or actuator;
- Digital smart agents are embedded, self-contained agents that consist of both a microprocessor to execute agent tasks and is self-aware of its environment space;
- Analogous agents consist of analogue sensors attached to a microcontroller that is responsible for the agency and communication processes. It is designed to bind a compatibility space and allow legacy devices to interface with the environment.

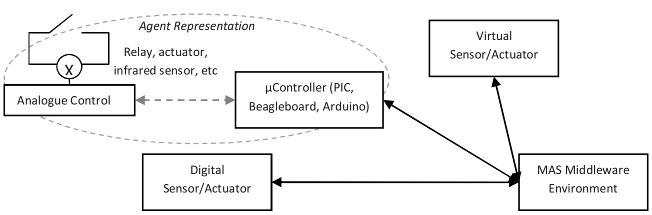
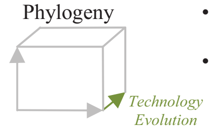
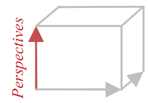
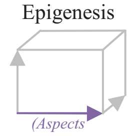


Figure 1: Middleware Agencies in BDI Framework

SANETs architectures for healthcare monitoring need to be service-oriented for composition, configuration and integration so the application can be designed efficiently from the data model, so the biomimetic model perspective can be projected onto a three dimensional space based on the POE Classification Model [1][2][20] as elaborated in Table 1. The POE model represents the different levels of organization, with POE standing for Phylogeny, Ontogeny and Epigenesis. In terms of the POE model, each software agent will encapsulate each of the different biomimetic models, in such a way that the functional scope of each agent is responsible for its own responsible parameters. For the same case in nature, the biological contexts for phylogeny, ontogeny and epigenesis are systemic processes that function independently from each other.

TABLE 1
POE MODEL AND SANET CORRELATIONS

Dimension	Context and Correlation
Phylogeny 	• *Biological Context:* Entail evolution of species genetics. • *SANET Correlation:* This relates to the implementation of heuristic problem solving algorithms (Cooperative EKMs) and the evolution of technology.
Ontogeny 	• *Biological Context:* Concerned with cellular growth process, multi-cellular organization, cellular division and differentiation from the parent to child cells. Each child cell processes a copy of the original genome. • *SANET Correlation:* The perspective of the domain space and calculation of EKM activation energies.
Epigenesis 	• *Biological Context:* This involves the adaptation and learning processes. The nervous, immune and endocrine systems are characterized by epigenesis. • *SANET Correlation:* This space corresponds to the facets or aspects of knowledge acquisition by responding to stimuli and weights adaption feedback.

II. DOMAIN ANALYSIS OF SANETS

A. Cooperative EKMs with Agent-based Architectures

Procedural controls are formed as a discrete set of commands to be used by reinforcement learning algorithms [18] to be selected from a library of heuristic functions for a distributed network in a healthcare concern. Reinforcement learning is driven by continuous control space functions [17], as indirect-mapping methods provide fluid decision choices than direct mapping. The accuracy in sensory stimuli control is important where external factors directly affect the network's robustness and reliability, allows for developing a feature map approach using co-operative EKMs with indirect mapping to improve the responsiveness of the tracking process [4][17].

By the direct-mapping technique, node inputs are mapped to sensory stimuli, with indirect-maps of sensory stimuli linked to a node with the utilization of control parameters, including energy discharge, signal strength and node roles as ordinary node, cluster head or location anchors. Meanwhile, by using the indirect-mapping technique, Continuous sensory stimuli space is mapped to the node; instead of direct-mapping that map continuous sensory stimuli space to the actual directives. Quality evaluators determine optimum clustering [5]. By using an indirect-mapping process, a continuous processing space is established for each sensor and its corresponding sensory component, so that there is a direct correlation of data parameters for each sensor in the SANET space.

Event predication can be achieved using linear trajectory models in Euclidean space [14]. However, multi-dimensional problems outside of Euclidean space are sacrificed as a result, inclusive of network interference and ensuring energy efficiency. By not factoring the domain concern of including the problem set into a singular process model, the problem scope increases exponentially [1].

The solution is to transform the views and decompose them into a singular map of the highest activation energies or stimuli, which is achieved once the maximum value of the integration matrix is calculated for all EKMs for each of the input stimuli received from the SANET's environment. Insufficient sensory controls can result in unexpected or undesirable outcomes, leading to possible faults in navigating a route to the gateway [17][18]. When EKMs are established in the weighted-sum ensemble, a similar problem of unsolvable outcomes also takes place. This can be solved by using an indirect EKM mapping method, whereby the control vector is manipulated indirectly via a control parameter space [17].

The environmental concern shown in Figure 2: Co-operative EKM Process [4] for a given SANET domain can be summarized in the following statement tasks:

- For initial state described by input vector u(0) in input space U, inclusive of the sensory perception;
- Adapt sequence of control vectors c(t), t=0…t−1, in sensor control space C and solve activation energies;
- With resultant goal state elaborated by u(T) ∈ U that adapts the structure for a desired objective, thus reacting to the stimulus and changing the input state.

Using a multi-objective approach with co-operative EKMs as the modeling function has been adopted, with a reinforcement learning technique chosen on the basis of the situation or context [17] in an agent-based domain space. Interleaved EKMs that cooperate and compete to self-organize can enable a node to optimize in managing clustering and routing dynamically, whereby the node's output control is less than the total variable control available. Euclidean and weighted-sum ensemble methods have detrimental outcomes, even though a continuous sensory control space is implemented [14].

B. *Multi-Objective Meta-Heuristic Algorithm (MMA)*

The paradigm of meta-heuristics is taking the optimum yielded results of selected heuristic methods that are suitable for the problem domain in a healthcare environment. In particular, nature-inspired functions are most suitable when considering the learning capability of the healthcare network that is suitable for patient prediction models. Unlike with trajectory functions, which are concerned with local thresholds to yield a result, bio-inspired functions take a holistic view of the dynamic, evolving system. In essence, by combining a multi-dimensional approach to analyzing a given dataset, we can enhance the regenerative learning capability for any given heuristic optimization model. Current experiments for SANET modeling examine genetic algorithms and Particle Swarm Optimization (PSO) [8], as they both implicit-based reinforcement learning methods that attempt to seek a long term advantage through a representation set of scalar rewards. A filtration process is then applied to the mapping data to clear erroneous and randomized data introduced as a result of the algorithmic calculations, allowing for a clearer weighting adaption once a response is made to the stimuli.

The application of the heuristic algorithm follows the approach of applying EKM principles to the problem domain in SANETs [5][8]. This requires the modeling map to be translated into a training vector to be processed against a scalar rewards vector, which reflects the optimum energy or routing condition; depending on the current environmental concerns of the SANET network. The number of evolutions to determine an acceptable result will affect the quality of the process, but there requires a balance between obtaining a quality evaluation, which requires more processing time and is power intensive, with minimizing the time to process the heuristic function for resource conservation. The implementation method for meta-heuristic functions in the experimental model is established procedurally in Table 2.

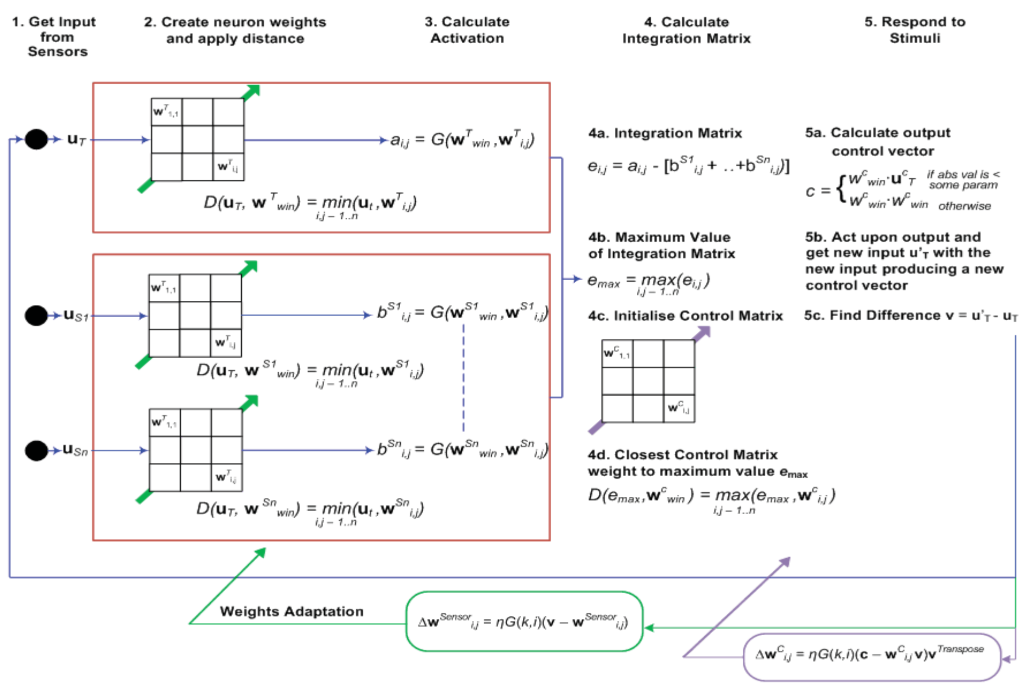


Figure 2: Co-operative EKM Process [4]

TABLE 2
POE-STAGED EXPERIMENTAL PROCESS

POE Stage	Experimental Process
Stage 1: Model Domain Environment (Phylogenical)	• This stage is about performing an Unsupervised Learning Heuristic on the environment. This involves modeling the environmental concerns to determine how the data should be organized for optimum clustering and routing mechanisms. • The current experiment considers the use of EKMs to model the SANET environment from the input sensory perception. This autonomous process occurs at the beginning.
Stage 2: Train for Environment (Ontological)	• This stage is about performing a Reinforcement Learning Heuristic. This allows the environment to be aware of its context, and learn from its own experience and that of its cooperative actors. • The experiment incorporates genetic algorithmic heuristics to achieve learning capability. Classical techniques such as brute-force analysis is computationally inefficient, and is infeasible to consider all outcomes that lead to an optimum solution, only the best-effort solution in time.
Stage 3: Refine Training Set (Epigenetical)	• This stage is about factorizing the Training Set. This optimizes the training set for a given learning heuristic to a singular vector, reducing invariability for long-term forecasting. • The current experiment considers generalized optimization techniques to reduce noise and other variability in the training set. This is necessary to select an ideal candidate that establishes the fitness condition for the SANET environment, such as maintaining the minimum energy condition and optimizing bandwidth.

III. EXPERIMENTAL PROCEDURE

The evaluation of co-operative EKMs on SANETs is executed using the framework conceived by Chaczko, et al [4]. The Jadex framework by Universität Hamburg, shown in Figure 3: Java Simulation Environment [5] allows for convenient monitoring and tracking of SANET events by pre-assigning event trajectories in the network field in an interactive manner.

Figure 3: Java Simulation Environment [5]

A. General Assumptions

- The topology of the SANET healthcare monitoring network is two-dimensional, such that altitude is constant and negligible between nodes.
- All nodes are powered at 100% capacity. Energy dissipation is calculated using inverse square law.
- The event trajectory is not predefined, such that the beginning and end points are calculated randomly using Fast Mersenne-Twister method.
- The network is considered to be interference free; as such RF communication concerns are not evaluated in the experimental model.

B. Experimental Method

The experiment is completed with the methodology by establishing the following simulation constraints:

1. A population of *n* nodes is distributed randomly via Fast Mersenne-Twister, in a two-dimensional network of 100m x 100m. Node populations tested include:
   a. 100; d. 1000; g. 4000;
   b. 250; e. 2000; h. 5000.
   c. 500; f. 3000;
2. An event trajectory is executed from a point in the network area; of which the test path course is either:
   a. *Linear Path:* A linear path consists of an event trajectory where the entry and exit point from the area is of constant gradient.
   b. *Arc-formation Path:* Arc-formation consists of an event trajectory where the entry and exit point will either be increasing or decreasing in gradient, forming a circle segment.
   c. *Pseudo-random Path:* A pseudo-random path using the Mersenne-Twister method combines 2(a) and 2(b) at various points throughout the trajectory, until it reaches the exit point.
3. The algorithm selects the route from the node in range of the approximate trajectory to be established to the sink; such that the closer the algorithm is to calculating the event path, the more optimum the route will be to establish successful negotiations.
   a. *Co-operative EKMs with PSO:* Co-operative EKMs use an indirect-mapping SOM map to train the control parameters in which to converge at the final trajectory point; in such a fashion to actively train the neural network to seek positive outcomes to determine a route from the trajectory's path to the sink.
   b. *Co-operative EKMs with Agent-based Architectures:* In conjunction with Co-operative EKMs, a filtrating mechanism is applied to the weights adaptation map to assist in the event tracking functions.

   In conjunction, the reinforcement learning heuristic applied to the SOM map as a training vector set, and a vector test set is applied to maintain accuracy of path estimation. Using Particle Swarm Optimization [8], the shortest Euclidean distance between the specific trajectory point and the nearest neighboring node is nominated within the routable path to the sink or health repository.
4. The experiment is executed for 1000 iterations to calculate the mean rate of successful identification of the trajectory's target point, when the simulated event exits the area:
   a. A maximum margin of error is a 2m x 2m area where final approximate point is found.
   b. A successful identification is where the final end-point is within a 95% confidence interval of the entire network. Any estimation outside of this threshold is identified as a failed identification.

IV. EXPERIMENTAL RESULTS

The results demonstrate that in comparison to co-operative EKMs with PSO utilizing agent-based architectures, the final results are positive when pseudo-random trajectory tracking is required. While standard Co-operative EKMs perform adequately in the given scenarios; co-operative EKMs demonstrates an improvement in the identification rate over standard co-operative EKM algorithms. This is evident with a greater node population, as the granularity of determining a nearest neighboring node to route is reduced for the fixed size of the network.

As shown in Figure 4: Experimental Results of Detection there is a 35% relative improvement in the average mean detection rates with agent-based optimization for the pseudo-random trajectory compared to standard co-operative EKMs. As co-operative EKM demonstrate improvement over passive learning techniques, current prediction rates are sufficient for routing estimation capability, which indicate the process of refining the training set for remodeling is necessary to improve the SANET routing condition.

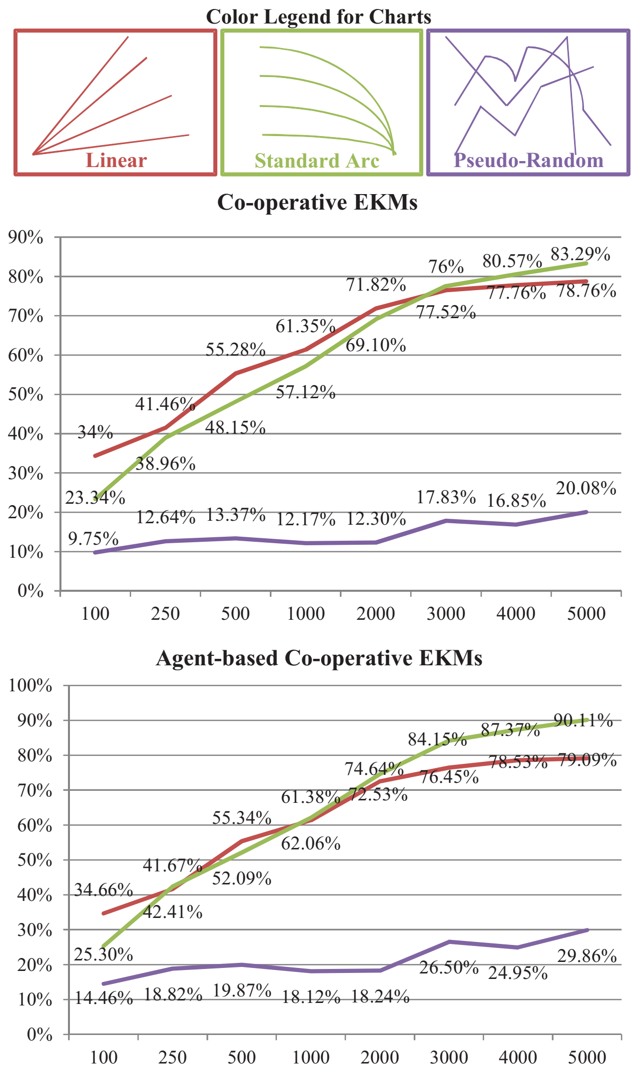


Figure 4: Experimental Results of Detection Success

The analysis of co-operative EKMs as shown below in Table 3 and 4, when assessed in terms of performance of pseudo-random tracking, requires more analysis into the algorithmic procedure. In particular, the thresholds established for determining positive or negative learning reinforcement is an issue that needs to be evaluated for an in-depth assessment. The tolerance levels used to calculate the thresholds is important, as subtle variations in tolerance may yield undesirable results. As a case in point, reducing tolerance levels too far will result in the inflexibility of the algorithm to adapt to changes the event trajectory; the corollary is that generous tolerance levels will yield undesirable tracking results when noise or faulty nodes produce invalid sensory data.

Furthermore, the use of Clifford algebraic forms can be used in a SANET system in terms of extending the geometric form of the network's geometric structure [14][15]. The quaternions of the network can be extended for 4th dimensional rotation groups, which serves as an ideal base for energy conservation and core attributes of a SANET network. Although the current simulation framework does not incorporate Clifford algebraic forms as an optimization technique, the modular design of the simulation environment will enable incorporation of this technique in the next iteration of the healthcare framework.

TABLE 3 AND 4

COMPARATIVE ASSESSMENT AND EVALUATION

CO-OPERATIVE EKMS WITH PSO

Assessment	Evaluation
Quantitative Assessment	• Demonstrates an indirect-mapping EKM can provide detection to optimize for local obstruction and global target identification concerns in a distributed sensor space.
Qualitative Assessment	• Results show a smoother tracking mechanism to monitor events in real-time, compensating for random events [17][19]. • Co-operative EKMS with PSO, in conjunction with an enhanced training set refinement mechanism, yields more consistent results as due to an optimal training vector.

CO-OPERATIVE EKMS WITH AGENT-BASED ARCHITECTURES

Assessment	Evaluation
Quantitative Assessment	• Shows that the filtration method can yield a noticeable improvement of 50% in detection rates for randomized routes. • The improvement in detection success is a result of the EKM estimator used when optimizing the neural weights, that compensates for noise introduced.
Qualitative Assessment	• Cooperative EKMs do not adjust to interference or noise introduced into the system, such that the final detection may be overcompensated and result in poor detection results. • Results show that Co-operative EKMs combined with agent-based architectures improves the tracking process by reducing noise and interference within the feedback loop [1][2].

As a consequence, the potential of Co-operative EKMs to identify events within a SANET network is evident; but as with all passive learning heuristic methods, a heuristic ensemble approach using MMA is necessary to train the algorithm to evaluate and determine the tolerance thresholds that are most suitable for the current conditions. The implementation of co-operative EKMs with alternative heuristic algorithms such as genetic algorithms will need to be considered in future to evaluate improvement in the mean identification rate. Furthermore, a feedback mechanism incorporating training set factorization is required to minimize error rates and ensure a consistent set of data outcomes, and allow for more fluid responses in the routing and tracking network functions.

V. Result Analysis

A. *Cooperative EKMs with Agent-based Architectures*

The notable variability in the identification rate indicates a need to improve the quality of training mechanisms to reinforce positive selection processes, so the aggregation of the final routing selection is optimal for the system environment. Furthermore, the implementation of refining the training set is necessary to ensure that the SANET modeling functions do not introduce internally generated erroneous data that will impact on the system's ability to make future predictions based on historical trends. The relative improvement of 50% on traditional cooperative EKMs is significant to note; with the aim being a yield in the trajectory projection to ensure results are within the 95% confidence interval in tracking projections. In particular, further examination is required to determine the trade-off between yielding an efficient route which will be more computationally intensive, or a best-effort route that will be more energy conservative. However, the distributed nature of SANETs means that computational calculations can take place for each routing hop, so that while the local calculations are considered for each route, a global picture is established for the entire route to the gateway or central healthcare repository.

VI. Conclusion

The method of adaptive SANET management for healthcare monitoring with co-operative EKMs coupled with agent-based architectures is beneficial, with the current results demonstrating indirect-mapping EKM generating more proficient routing and clustering conditions when compared to direct-mapping EKMs. Furthermore, the control parameters of the indirect-mapping EKM can be enhanced with Rao-Blackwell algorithms to allow convergence and better optimization, with choices in the reinforcement learning technique providing context-aware outcomes to improve the reinforcement learning capability for patient monitoring.

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