

## SPECIAL ISSUE PAPER

# A stochastic game net-based model for effective decision-making in smart environments

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### SUMMARY

Internet of Things (IoT) in today's smart environments has many applications in gerontology, health care, transportation, and smart cities. Many challenges still exist in developing IoT-based smart environments. Dynamic generation of action strategies based on multiple IoT object's input is one of the major challenges. In this paper, stochastic Petri nets and game theory are combined to create stochastic game nets (SGNs) for IoT-based smart environment where each IoT device acts as a player with predefined place and action sets. Complete SGN will be created dynamically using individual sensor SGNs which will make IoT-based smart environments highly interoperable and scalable. Proposed model is used to predict activities performed by two-single person in their respective home with more than 70 sensors. Simulation results show suitability of proposed model in smart environments. Proposed model is tested for smart homes, but it can be used in any IoT-based smart environment. Copyright © 2016 John Wiley & Sons, Ltd.

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### 1. INTRODUCTION

Cloud computing has emerged as an important paradigm in current cyberspace environment. Most of the reputed organizations such as Microsoft, Google, and IBM are highly investing in cloud computing infrastructure and applications development. Cloud computing has become a vital link in the emergence of new technologies that requires high and varying IT resources demand. Increase in number of smart devices (smart phones, smart sensors, and so on) and advances in mobile cloud computing unlocked many research areas for real-time data analysis and decision-making. Because of virtually infinite number of resources provided by cloud computing, it has become possible to analyze real-time data of trillions of sensors deployed across cities. Multiple cities will involve millions of smart devices connected to each other and generate huge amount of data in real time, which gave rise to new paradigm known as Internet of Things (IoT). IoT has become a tempting technology in today's smart information environment. In 1998, Kevin Ashton mentioned IoT first time in his presentation related to future of sensors [1]. In 2005, a formal definition of IoT was introduced by the International Telecommunication Unit in its report [2]. In 2005, cloud computing technologies were still in its early stages, and traditional IT environments were not able to meet resource demand of proposed IoT technology. But with successful implementation of cloud computing, IoT becomes a highlighted research area that combines multiple technologies such as sensor networks, big data analytics, and cloud computing [3]. IoT is a connection of digital devices (also known as smart devices or IoT objects) to the

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Internet so that they can sense environments, formulate results, and communicate effectively to humans or to other digital devices [3–5]. IoT has many application areas such as healthcare services [6], emergency services [5], manufacturing [7], industry [8], urban planning, and many more.

By combining the IoT vision with cloud computing, smart environments can be developed, which can consist of millions of nodes at multiple end terminals such as homes, hospitals, supermarkets, and other terminals. Millions of smart devices employed in different end terminals can sense very large number of attributes simultaneously. Concurrent accessing of large amount of attributes will lead to more reliable and accurate decision-making in smart environments. But, such a complex system should have three key characteristics for effective decision-making: (1) Quick diagnosis of smart environment when any sensor creates an alert. (2) Creation of strategies to be adopted in real time. (3) Learning new strategies with time based on user's activities. Combination of stochastic Petri nets (SPNs) and game theory will be promising in formulating optimal solutions for previously said smart environments.

Stochastic Petri nets are model-based stochastic networks, which are used to model dynamic behavior of any complex system [9]. SPNs are dynamic in nature because they use probabilistic models defined by the theory of Petri nets. SPNs are capable of studying multiple attributes of a complex system such as performance, reliability, and security. Stochastic reward nets are generalized form of SPNs by associating reward for each transition performed in SPN [9]. Total reward generated can be used to derive complex decisions for any system. Stochastic game theory (SGT) has been extensively used for studying network security [10]. A two-player game is modeled by most of the researchers for computing best case response strategies (also known as Nash equilibrium) depending upon strategies played by attacker and network administrator [11, 12]. However, four key challenges of SGT prevent its successful implementation in the field of IoT: (1) SGT does not have modeling power to model games with large number of players and mixed strategies being played. (2) Large number of state transitions in IoT environment makes it impossible to study dynamic behavior of the system for calculating the Nash equilibrium. (3) In SGT systems, models are developed for all scenarios including many unrelated scenarios. Proposed system should model and study subset of scenarios which are important to final decisions so that available resources are effectively utilized. Removing unrelated scenarios are nearly impossible in SGT. (4) In IoT-based systems, a set of priorities should be used for all devices. Using SGT, it is not possible to provide different priorities to all the players. SGT when combined with SPNs can solve all of earlier stated challenges by creating stochastic game nets (SGNs).

Developing smart environments using SGN provide three main benefits over traditional methods: (1) SGNs provide effective structuring mechanism for smart environments using Petri networks. This provides better analysis of relationships, performance, and reliability with minimal ambiguity. (2) SGN will make smart environments as  $n$ -player game with each IoT device acting as an individual player with finite set of actions. In SGN, only triggered or required sensor will be used to create dynamic  $n$ -player game. So, SGN provides appropriate method to represent available strategies and payoffs for whole system as well as to each IoT device. (3) SGN allows the system to take decisions using multiple attributes in a timely and effective manner. Moreover, SGN in smart environments will provide deeper understanding of scenarios, strategies, integration of IoT devices, and calculation of best response strategy (also known as Nash equilibrium).

The motivation of the paper is the development of methods of effective decision-making in smart environments combining SPNs and game theory. Major novel contributions of the proposed work in this paper are as follows:

- Modeling smart environments on the basis of  $n$ -player game theory where each IoT device deployed in the house acts as an individual player. Each device has payoffs associated with its each action performed.
- A novel framework using SPNs is used to analyze and model the  $n$ -player game for IoT devices.
- Mathematical foundation has been developed for using SGNs in IoT-based smart environments.
- Testing proposed methodology in a smart home environment using multiple sensors.

To the best of our knowledge, this is first attempt to use game theory and SPNs for decision-making in complex IoT-based environments.

Rest of paper is structured as follows. Section 2 provides some related work for cloud computing in IoT and use of game theory in IoT domains. Section 3 provides methodology and theoretical foundation for the concepts used in this paper. Section 4 evaluates the proposed model using a use case of smart home containing multiple sensors. Section 5 provides experimental results and discussion of proposed model. Section 6 concludes the paper.

## 2. RELATED WORK

Definitions and applications of concepts used in proposed model are discussed in Section 1. However, this section provides some of the notable contributions of these concepts in the published literature.

### 2.1. Cloud computing for smart environments

Relation of cloud computing and IoT is studied and mentioned by many researchers. IoT environments require cloud computing to process very large amount of data collected in real time from millions of sensors nodes. However, research on different smart application development areas using cloud computing and IoT together has been found extensively in literature. Important application research using IoT technologies over cloud computing is land resource supervision [13], water risk management [14], physical human security [15], smart chemical industry [16], smart environment monitoring [17], smart parking lot [18], smart traffic management [19], smart home [20], [21], assembly modeling system [22], smart manufacturing system [23], smart healthcare [24], and smart agriculture [25–27].

Apart from application perspective, development of architectures for integration of cloud computing with IoT environment is studied by many researchers. Integration frameworks were proposed which positively highlighted the need of cloud computing in IoT environments [28–34]. In 2015, Renner *et al.* [35] discussed the challenge of transferring IoT data to cloud computing for processing. They proposed to use resource power of smart device also to pre-process the data before sending it to cloud. In 2015, Dai *et al.* [36] provided a security framework for cloud computing in IoT environments. They created a trusted execution environment for cloud end computing security for IoT devices. In 2015, Shaoling *et al.* [37] developed an ant colony-based energy consumption model for cloud computing environment using IoT devices. In 2015, Villari *et al.* [38] suggested that lifecycle management of sensors is very important for any IoT-based smart environment. Sensors should connect to cloud automatically and securely. They performed a self-identification process which securely auto-configure sensors with cloud. In 2015, Botta *et al.* [29] surveyed different architectural and application scenarios of cloud computing and IoT. They proposed a new name ‘CloudIoT’ for IoT platforms using cloud computing. In 2015, Amato *et al.* [39] analyzed the need and importance of big data in IoT environments using cloud computing. They argued that IoT environments will generate very large amount of data which need to store, manage, and analyze for which big data analytics are necessary. In 2014, Li *et al.* [40] used stochastic bag of task-based scheduling for achieving energy efficiency in heterogeneous computing systems. In 2014, Mei *et al.* [41] proposed an algorithm which reduces the duplication of resources for critical tasks. Their algorithm provides better resource scheduling in cloud with less number of redundant tasks. In 2014, Kang *et al.* [42] designed a smart storage system in cloud computing for IoT environments. This storage system consists of four layers and provided better scalability. Similarly, Jiang *et al.* [43] proposed a storage framework for IoT systems developed on cloud computing. Their system was compatible to handle structured and unstructured data using Hadoop file system and initial assessment proved its effectiveness.

### 2.2. Game theory for Internet of Things

In 2010, Da-wei and Geng [44] used repeated game theory-based secret sharing in an IoT environment by providing appropriate payoffs of sharing the secret to each node. In 2011, Hu *et al.* [45] found a Nash equilibrium using non-cooperative game theory between network resource bidding and creditability of nodes in IoT environment. In 2011, Tang *et al.* [46] proposed an energy-efficient

scheduling algorithm to schedule task on grid using stochastic methodology. In 2012, Liu *et al.* [47] proposed game theory for detecting malicious nodes in an organizational dominant IoT network. In 2013, Ding *et al.* [12] developed a non-cooperative game strategy for identifying the internal attacks in a sensor network of IoT environment. In 2013, Lan *et al.* [48] used Stackelberg game model for negotiation between pricing and resource allocation in heterogeneous IoT networks. In 2013, Wang *et al.* [49] provided secure data fusion based on game theory. In 2014, Li *et al.* [40] used stochastic bag of task-based scheduling for achieving energy efficiency in heterogeneous computing systems. In 2014, Fuhong *et al.* [50] argued that energy consumption and bandwidth used are two inversely proportional attributes of any IoT device so a trade-off should be maintained. They used the concept of game theory to calculate a Nash equilibrium so that effective allocation policies can be implemented. In 2014, Zuo [51] used repeated game theory to detect intruder in IoT-based smart environments. In 2014, Liu *et al.* [52] developed a framework for congestion control in multilayer data transmission for IoT environments. They designed a two-step game model for balancing cooperation of nodes and price of information provided by them. In 2015, Kumar *et al.* [11] evaluated the performance of Bayesian coalition game for network of IoT devices interconnected to each other. They used the concepts of game theory and learning automata to formulate different strategies and their payoffs. In 2014, Li *et al.* [53] proposed to form a game for scheduling linear deteriorating jobs where players are job owner and machines are strategies. Results indicated the effectiveness of proposed game theory-based scheduling. In 2015, Liu *et al.* [54] demonstrated the use of game theory for making cloud service reservations in any cloud computing environment.

In 2012, Lv and Zhang [55] studied the profit distributions among operators in IoT environment using game theory. In 2012, Lv *et al.* [56] discussed the competition and cooperation between participants in any industrial supply chain management based on game theory. In 2013, Li *et al.* [57] discussed the pricing scenario of IoT environment with three stakeholders, which are consumer, intermediates, and information provider. They selected the pricing of stakeholders based on a Stackelberg game by optimizing strategies for intermediates and information providers. In 2013, Zhang [58] used evolutionary game theory and multi-agent simulation to find Nash equilibrium for operators and system integrators cooperation with each other in an IoT environment. In 2014, Qi and Bi [59] argued that there is insufficient relationship between consumer and core business for green supply chain management. They derived an evolutionary game strategy to find a stable state between both parties so that appropriate actions can be taken to manage green supply chain effectively.

### 3. METHODOLOGY AND THEORETICAL FOUNDATIONS

Several methods were proposed in many relevant literatures to derive effective decisions from any IoT-based environments. Proposed work uses combination of SPNs and game theory to model and efficiently make decision in any IoT-based smart environment. Figure 1 shows the flow of proposed framework for making any decision in any smart environment. Each sensor has a stored SGN. Every time a sensor is triggered, its SGN is combined to form a complete SGN. Based on complete SGN created and game theory, final decision will be taken. Final decision will be communicated back to sensors or concerned user as required by the application.

In proposed methodology, each IoT device is considered as a player in  $n$ -player game scenario. Each IoT device has certain set of actions to perform, and payoff is associated with each action. The set of actions by IoT devices can be combined in a graph to form a perfect information extensive form game. Payoffs can be calculated using rewards at each state of every IoT device. Any IoT-based smart environment can be represented as perfect information-based extensive form game because of two main reasons: (1) Time at which any IoT device is triggered can be easily stored to form a sequence of events. IoT device can be periodic based, trigger based, or both. In every type of IoT device, case sequence, and time are associated with the performed action. (2) Decision-making block will have information about output and current state of all IoT devices, so it is a perfect information game.

Stochastic Petri nets consist of a bipartite graph with places and transitions. Directed arcs connect places to the transitions and vice versa. Input arc connects place to transition, and output arc connects transition to place as shown in Figure 2.

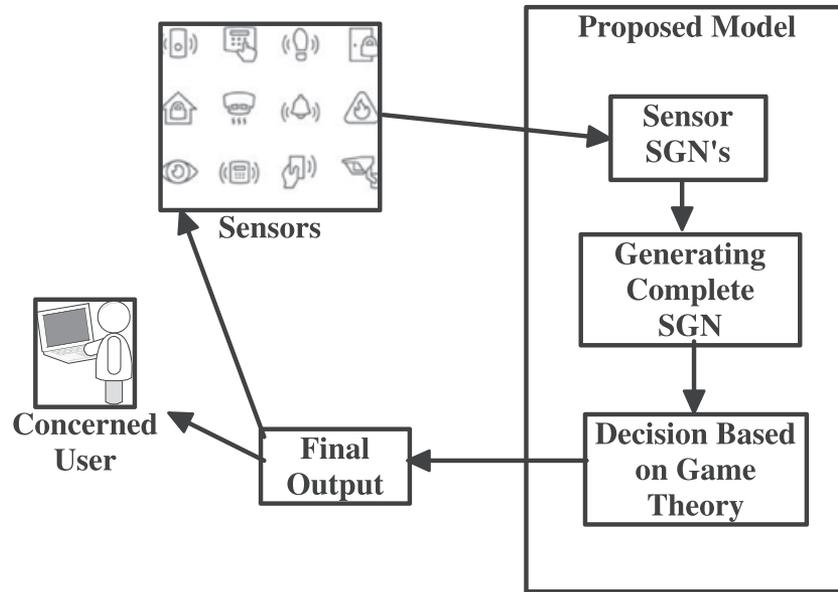


Figure 1. Flow of proposed model.

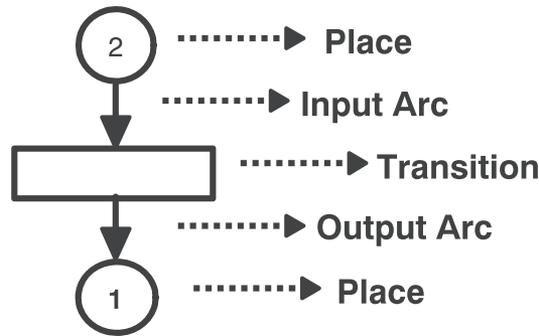


Figure 2. Simple stochastic Petri nets graph.

Tokens are associated with places in SPN network. Firing of token takes place from one place to another after fulfillment of certain condition present in transition. Marking is carried out to know number of tokens present in any place, and it is represented as  $\#(P1)$ .  $\#(P1)$  shows the cardinality of tokens present at place P1. Guard function is used in every transition. It evaluates the firing of tokens from one place to another. Token will be fired only if guard function is true in the transition. Stochastic game net created by combining game theory with SPN is used to model the graph of proposed perfect information extensive form game for any IoT environment. Next sections describe the theoretical foundations for the proposed methodology.

### 3.1. Stochastic game nets for Internet of Things-based environment

#### Definition 1

Any IoT device (termed as a player in rest of paper) based smart environment can be modeled to form a SGN with eight tuples which are

$$SGN = \{N, A, P, Z, T, \pi, \mathbb{R}, U\}$$

where,

- $N=(1, 2, 3 \dots \dots n)$  is set of IoT devices connected into a smart environment.

- A is single set of actions available to smart environment. System will choose one of the actions based on calculated payoffs.
- $P=(1, 2, \dots \dots m)$  is a finite set of places each IoT device has in its graph.
- Z is set of terminal places such that  $Z \cap P = \emptyset$ .
- $T = T^1 \cup T^2 \cup \dots \dots \cup T^k$  denotes finite set of transitions available for all IoT devices and  $T^k$  represents the set of transitions for the  $k^{th}$  device.
- $\pi : T^k \rightarrow [0, 1]$  denotes the probability of choosing any transition from all available transitions and  $\pi(T_1^k) + \pi(T_2^k) + \dots + \pi(T_n^k) = 1$ .
- $\mathbb{R} : T \rightarrow (r_1, r_2, \dots \dots, r_N)$  denotes the reward rate associated with each transition taken by each IoT device.
- $U = (u_1, u_2, \dots \dots, u_N)$  denotes the utility function of each IoT device.

In the representation stated earlier of any smart environment using SGN, a token  $t$  placed in place  $p$  represents current state of that IoT device. Also, each token  $t$  in place  $p \in P$  of any IoT device will have a reward vector associated with it. Reward vector for IoT devices can be represented as

$$r_p(t) = \{r_p^1(t), r_p^2(t), \dots \dots r_p^k(t)\}$$

where  $r_p^k(t)$  is the reward of player  $k$  at place  $p$  for the token  $t$ . Each IoT device will also generate certain rewards

$$R(t) = \{R^1(t), R^2(t), \dots \dots, R^N(t)\}$$

where  $R^k(t)$  is the reward of  $k^{th}$  IoT device which will be recorded in token  $t$  using  $r_p(t)$ . A transition  $t \in T$  at any place  $p \in P$  will be enabled only if state  $p$  has any token in it and it will be represented using marking as  $M(p) \neq \emptyset$ .

*Definition 2 Action set and place set of any Internet of Things device*

Let  $T^k$  and  $P^k$  represent the action set and place set of player  $k$ , respectively. Then, place set of IoT device  $k$  can be represented by union of all actions that IoT device can take from any state  $p \in P$  which can be represented as

$$P^k = \bigcup_{t \in T^k} p_t^k,$$

where  $p_t^k$  is the action  $t$  taken by player  $k$  at place  $p$ . Similarly, action set can be represented as

$$T^k = \bigcup_{p \in P^k} t_p^k.$$

*Definition 3 Strategy and strategy set of Internet of Things devices*

Strategies are the set of actions that any IoT device will or can take during its functioning. Strategies are called mixed strategies when there is certain probability associated with selection of each strategy. Let  $S^k$  be a mixed strategy of  $k^{th}$  IoT device. Then,

$$S^k = [\pi(t_1^k), \pi(t_2^k), \dots \dots, \pi(t_w^k)]$$

where  $\pi(t_1^k)$  is the probability of choosing action  $t_1$  for IoT device  $k$  and  $w$  is the total number of actions available that is  $w = |T^k|$ . Now, if current place of token is associated with the strategies, then total mixed strategies can be represented as

$$S^k = \left[ \pi \left( t_{p_1 i_1}^k \right), \dots, \pi \left( t_{p_1 i_{|p^k|}}^k \right), \dots, \pi \left( t_{p_{|p^k|} i_{|p^k|}}^k \right) \right]$$

where  $\pi\left(t_{p_1 i_1}^k\right)$  is the probability of strategy  $i_1$  to be played at place  $p_1$  by IoT device  $k$ . Strategy set of whole game with  $N$  players will be  $S = (S^1, S^2, \dots, S^N)$  where  $S^l$  is the strategies of first IoT device.

### 3.2. Corollary 3.1: probability of all choices

Sum of probabilities of all choices available at any node  $p \in P$  will be one which can be represented as

$$\sum_{t_i \in t_p^k} \pi\left(t_{p, i}^k\right) = 1$$

### 3.3. Corollary 3.1: Terminal nodes

At the terminal nodes, action set of every IoT device will be empty, and final payoff will be calculated. So, for  $k^{\text{th}}$  IoT device, any terminal node  $z \in Z$  will have empty action set represented as  $\emptyset_z^k$ . Utility function  $U^k(R^k(t), p_0)$  of  $k^{\text{th}}$  IoT device starting from initial node  $p_0$  will be reduced to  $U^k(R^k(t))$  at terminal node and will result in calculation of final payoff.

#### Definition 4 Reward calculation

Reward received by  $k^{\text{th}}$  IoT device at any place  $p$  can be calculated as  $R^k(p^w) = \sum_{o_i \in O} r_p^k(o_i) + \sum_{t_j \in T^w} r^k(t_j)$

where  $O$  is the token set at the place  $p$  at time instant  $w$ ,  $T^w$  is the total number of tokens passed within the time span  $w$ . To finish game in finite time, a discounted factor  $\Delta \in [0, 1]$  is also added.

Every SGN of IoT device has levels to reach its terminal node. At any timestamp  $w$ , reward will be only calculated for the levels which token has completed. So, when playing any strategy  $s$  and token has completed  $m$  levels of SGN, then its reward will be calculated using utility function of only  $m$  levels. Expected utility of IoT device  $k$  from current time  $w$  can be calculated as

$$\begin{aligned} U_w^k(\pi, p^w) &= E\{R^k(p^w) + \Delta R^k(p^{w+1}) + \Delta^2 R^k(p^{w+2}) + \dots + \Delta^m R^k(p^{w+m})\} \\ &= E\left[\sum_{n=0}^m \Delta^n R^k(p^{w+n})\right] \end{aligned}$$

Expectation operator  $E$  calculated the mean of probability used for selecting the transitions in SGN. So, if any IoT device  $k$  choose to play an action with probability,  $\pi^k(p^{w+n})$  will receive the reward as  $R^k(p^{w+n})$ . Reward at any place  $p$  can also be calculated using the probabilities as

$$R^k(p) = \sum_{t^1 \in T^1, \dots, t^n \in T^n} \{\pi^1(p, t^1), \pi^2(p, t^2), \dots, \pi^n(p, t^n) r^k(p; t^1, \dots, t^n)\}$$

where  $r^k(p; t^1, \dots, t^n)$  is the reward received by the player  $k$  at place  $p$  if player chooses certain set of transitions from  $t^i, i = 1, 2, \dots, N$ .

### 3.4. Dynamic stochastic game net

When any IoT device senses some critical data such as door bell or fire in any smart home environment, it will generate a trigger. After any appropriate trigger, either creation of dynamic SGN will be started or SGN of new triggered device will be added to the dynamic complete SGN. Sometimes one IoT device can demand the value of another IoT device based on desired problem in hand. This section will discuss the theoretical foundation of constructing dynamic SGNs based on perfect information for multiple IoT devices in any smart environment.

#### Definition 5 Formal definition of stochastic game net with perfect information

A multilevel SGN of  $N = \{1, 2, \dots, n\}$  IoT devices with perfect information is a tree-based graph  $G = (V, F)$  for which

- $V$  is the set of vertices of SGN  $G$  and  $F$  is set of edges which maps vertices to their next direct successors. If  $F_v = \emptyset$  for any  $v \in V$ , then  $v$  is the terminal node.

- There is partition of vertex set  $V$  into  $(n + 1)$  disjoint sets  $V_1, V_2, \dots, V_n, V_{n+1}$  is defined, where  $V_i, i \in N$  is the set of vertices of  $i^{th}$  IoT device and  $V_{n+1} = \{i : F_i = \emptyset\}$  is the set of terminal nodes.
- At each vertex  $v \in V$  of SGN  $G$ , a unique real-value reward is defined, which will help in calculating final payoffs at the terminal nodes.

*Definition 6 Constructing complete stochastic game net generation*

Level 0: When any IoT device is triggered first, complete SGN  $G$  is the same as triggered IoT device SGN graph with initial vertex  $v_o$ . Let the sequence of triggering of IoT is for total  $n$  IoT devices which is stored in a triggered list represented as  $TL = \{I_0, I_1, \dots, I_n\}$ . Let  $L$  be the set of edges used to join two SGN of different IoT devices.  $L_{ij}$  represents the linking edge between  $i^{th}$  IoT device and  $j^{th}$  IoT device. Payoffs will be calculated for this graph using Definition 4, and actions will be taken from action set explained in Definition 1.

Level 1: After the creation of Level 0 of SGN  $G$ . Now, IoT device  $I_0$  has following three options:

- No further action: If  $I_1 \notin TL$ , that is, there is no element in the triggered list, so decision should be made based on available SGN and wait for other sensor to be active. Game will move to any one terminal node of triggered device  $I_0$ .
- Add SGN: If  $I_1 \in TL$  then SGN of  $I_1^{th}$  IoT device should be added to complete SGN  $G$ .  $I_1^{th}$  IoT device SGN will be added to current state vertex of SGN of  $I_0^{th}$  IoT device. Now, game will end at terminal node of SGN of  $I_1^{th}$  IoT device.
- Break SGN: If  $I_1$  has been removed form  $TL$ , then SGN of  $I_1^{th}$  IoT device should be removed from the complete SGN  $G$ . Now, game will again restart at connecting edge of SGN's of  $I_1^{th}$  and  $I_0^{th}$  IoT device.

According to previously explained three actions available with Level 0 device, number of vertices  $V$  available in complete SGN  $G$  will change as

$$\begin{aligned} V &= V; && \text{If No action is taken.} \\ V \cup V(L_{01}); &&& \text{If new SGN has been added and} \\ V &= V - L_{01}; && \text{If SGN has to be removed} \end{aligned}$$

Similarly, Level 2 will be created using perfect information from Level 1. Suppose SGN  $G$  moves to level  $t$  ( $0 < t \leq l$ ) where  $l$  is maximum possible levels of SGN  $G$ . So a SGN has been created from Level 0 to Level  $t-1$ . Let  $\{v_o, v_1, \dots, v_{t-1}\}$  be the set of vertices which form a path from initial vertex  $v_o$  to terminal vertex  $v_{t-1}$  of Level  $t-1$ . By the construction, for all initial vertexes of connected SGNs, there will be respective linking edges  $L = \{L_{01}, L_{12}, \dots, L_{(t-2)(t-1)}\}$ . Now,  $L_{(t-1)(t)}$  will be defined using three possible actions available to SGN at level  $t-1$ . Number of vertices will change as follows:

$$\begin{aligned} V^t &= V^{t-1}; && \text{If no action is performed and there is no } L_{(t-1)(t)} \text{ link so} \\ &&& \text{game will end at terminal nodes of } (t-1)^{th} \text{ IoT device.} \\ V^t &= V^{t-1} \cup V(L_{(t-1)(t)}); && \text{If new SGN has been added at stage } t. \\ V^t &= V^{t-1} - V(L_{(t-2)(t-1)}); && \text{If previous SGN is removed at stage } t. \end{aligned}$$

Hence, for each vertex  $v \in V$  in complete SGN  $G$ , a unique link set  $L^v$  will always be defined. If current vertex of SGN graph  $G$  at any time instant  $t$  is  $v_t \in V$  and  $v_t \notin V_{n+1}$ , then graph has not reached the terminal nodes so system should continue the transversal of graph based on all inputs. Whereas, if current vertex  $v_t \in V$  and  $v_t \in V_{n+1}$ , then system is in terminal node of SGN  $G$  so system should choose an action from action set available as explained in Definition 1. System can continuously add SGN's, remove SGN's, and make decisions throughout the lifecycle of any smart environment based on previously explained theoretical foundation.

*Definition 7 Nash equilibrium of dynamic SGN*

Given  $N$  IoT device-based dynamic constructed SGN graph  $G$  then a mixed strategy Nash equilibrium vector is

$$S^* = \{S^{1*}, S^{2*}, \dots, S^{N*}\}$$

such that total reward of SGN graph  $G$  for any  $k^{th}$  player is

$$R^k \left( S^{1*}, S^{2*}, \dots, S^{(k-1)*}, S^k, S^{(k+1)*}, \dots, S^{N*} \right) \geq R^k \left( S^{1*}, S^{2*}, \dots, S^{(k-1)*}, S^k, S^{(k+1)*}, \dots, S^{N*} \right)$$

where  $S^k$  is any alternative strategy for player  $k$  than the nash equilibrium strategy  $S^{k*}$ .

*3.5. Corollary 7.1: For any dynamic constructed SGN = {N, A, P, Z, T,  $\pi$ ,  $\mathbb{R}$ , U}, If  $N < \infty$  and two sets P and T are finite, then there always exist a Nash equilibrium for setting of a mixed strategy*

It is already proved that any game with perfect information will have certain mixed strategies that will result in at least one Nash equilibrium. In current context, only one thing is to prove that dynamic constructed SGN  $G$  is a game with perfect information itself. Here, each IoT device acts as a player with finite number of actions describe in action set, and states in its individual SGN are also finite. Rules of game will be translated to transition firing rates with certain probabilities. Dynamic constructed SGN has knowledge of state of all IoT devices that proves the existence of perfect information paradigm. Therefore, dynamic constructed SGN for IoT devices in any smart environment fulfill all requirements of extensive form game with perfect information. Hence, there exists a Nash equilibrium for certain set of mixed strategies.

*3.6. Corollary 7.2: Sub-game perfection in dynamic SG stochastic game net*

Assume the SGN  $G$  constructed is of length  $l$ . To find the optimal behavior of any IoT system, sub-game perfection method is used. Sub-game in any smart environment is individual IoT device and if each IoT device is in its optimal state then whole system will also be in optimal state. Reward calculation equation formulated in Definition 4 states that reward calculated for each player is formed by its state space and actions sets. Therefore, an optimal solution can be found for each sub-game of complete SGN  $G$ . So, overall Nash equilibrium can be constructed by obtaining Nash equilibrium in each IoT device individual SGN. Path created by joining optimal path of each IoT device SGN will be the optimal path of complete SGN  $G$ .

## 4. SMART HOME

Smart home is taken as a use case to experimentally test the proposed model of effective decision-making in any smart environment. A sensor dataset developed in MIT by Tapia *et al.* [60] is used for designing the experimental evaluation of the model. Tapia *et al.* [60] collected dataset of two-single person homes using more than 70 sensors placed in different location of home. Placement of sensor is shown in Figure 3 provided by Tapia *et al.* [60] for collecting the sensor data.

GamePlan [61] software kit is used to design the game theory-based detection of activities performed by user. SGN and reward function table is prepared for each sensor placed in both the homes. Each time a sensor is triggered, its SGN is combined with already existed SGN using the methodology explained in Definition 6. Nash equilibrium is calculated every time complete SGN has been updated. Sub-game perfection method provided in GamePlan software is used to calculate the Nash equilibrium with each sensor being a sub-game itself. In the context of current smart environment, Definition 1 can be reformed as follows: Smart home environment with multiple sensors can be modeled to form a SGN with eight tuples which are

$$SGN = \{N, A, P, Z, T, \pi, \mathbb{R}, U\}$$

where

- $N = (1, 2, 3 \dots n)$  is set of sensors placed in the homes which are 77 in first home and 84 in the second home.
- $A$  is single set of 45 activities performed by the users in their homes.
- $P = (1, 2, \dots 5)$  is a finite set of places in the SGN of each sensor placed in the home. In current context of smart home, number of places in SGN of different sensor ranges from 1 to 5.



Figure 3. Location for placement of sensors in two homes [60].

- $Z$  is set of terminal places of SGN of each sensor. Each terminal node has an activity associated with it.
- $T = T^1 \cup T^2 \cup \dots \cup T^k$  denotes finite set of transitions available for all sensors, and  $T^k$  represents the set of transitions for the  $k^{\text{th}}$  sensor.
- $\pi: T^k \rightarrow [0, 1]$  denotes the probability of choosing any transition from all available transitions and  $\pi(T_1^k) + \pi(T_2^k) + \dots + \pi(T_n^k) = 1$ .
- $\mathbb{R}: T \rightarrow (r_1, r_2, \dots, r_N)$  denotes the reward rate associated with each transition taken by each sensor.
- $U = (u_1, u_2, \dots, u_N)$  denotes the utility function of each sensor.

Next section provides important results and discussion on usefulness of proposed method in any smart environment.

## 5. PRELIMINARY EXPERIMENTAL RESULTS AND DISCUSSION

Different set of activities performed by each user along with the timestamp and complete SGN created for separate activities are stored for two weeks. Stored complete SGN for each separate activity helped the proposed model to identify sequence of activities performed by the user. Repeated sequence of activities from first week are extracted and compared with activities of second week. Certain fluctuations in the activities performed by users were also found and recorded. Proposed model also generates alerts after detecting an activity performed by the user. All the results generated by implementing MIT's sensor data in GamePlan software using dynamic SGN approach are presented in next section.

5.1. Results

Different measures such as activities performed, sequence of activities, fluctuations, and alerts are generated from sensor data provided by Tapia *et al.* Table I and Figure 4 provided the average number of activities and different activities detected by proposed model as compared with Tapia *et al.* Table II listed top three activities detected by proposed model of both the persons.

Sequence in which activities are performed is very important in any smart environment. Fluctuations can be easily predicted when system is aware of sequence in which an activity should be performed. In proposed model, complete SGN has been updated with newly triggered sensor SGN using methods explain in Definition 6. Table III shows the total sequence found in sensor dataset for set of three and five sequence size. Sequence size in this context is the number of sensor triggered not the activity. Figure 5 shows the number of sequences identified for both Persons 1 and 2.

Based on the sequences stored using complete SGN of Week 1, fluctuations are predicted for Week 2. Most common sequence of Week 1 data were identified and stored with their respective timestamp. These sequences are compared with sequences of Week 2 within same timestamp. Margin of timestamp used was 15 min. Figure 6 shows the number of fluctuations identified by proposed

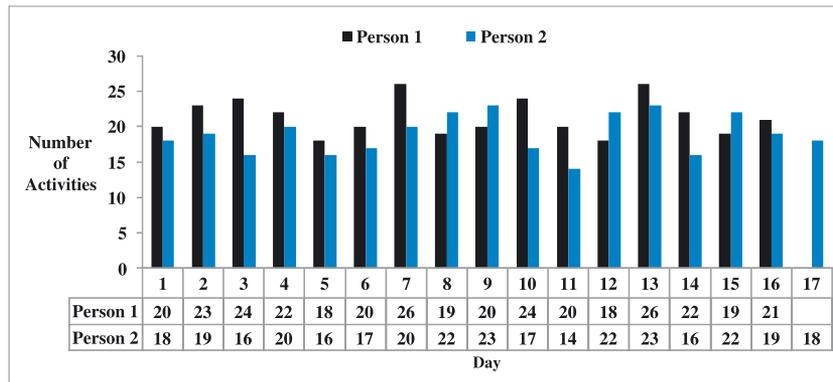


Figure 4. Number of activities performed each day.

Table I. Set of activities detected by proposed model.

	Tapia <i>et al.</i>		Proposed model	
	Person 1	Person 2	Person 1	Person 2
Average activities	17.8	15.5	21.3	18.9
Different activities	22	24	31	38

Table II. Top three activities performed by both person.

	Activity 1		Activity 2		Activity 3	
	Name	No.	Name	No.	Name	No.
Person 1	Toilet	81	Medication	64	Dressing	55
Person 2	Toilet	67	Preparing lunch	33	Preparing breakfast	30

Table III. Number of sequences identified in sensor dataset.

	Person 1		Person 2	
	3	5	3	5
Sequence size				
Average number of sequence per day	61.5	10.6	75.7	14.7
Different sequences	72	14	64	13

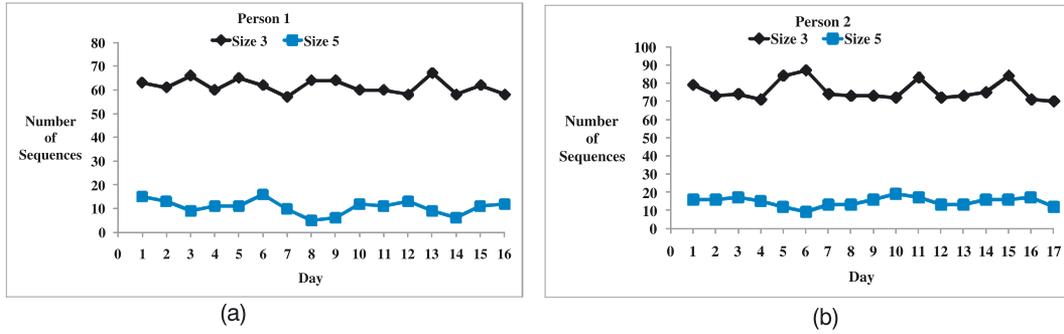


Figure 5. Number of sequences identified in sensor data for size three and five of (a) Person 1 (b) Person 2.

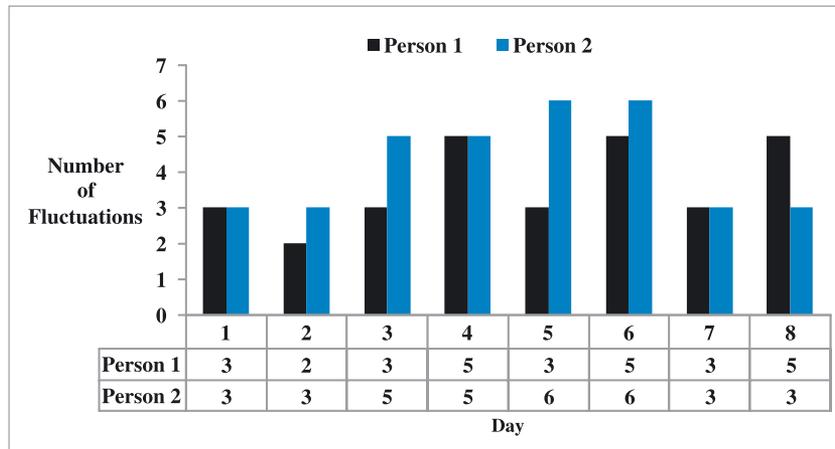


Figure 6. Number of fluctuations recorded in Week 2 data.

model from Week 2 sensor data. Proposed model also generates alerts based on total reward calculated from every complete SGN is created. Table IV listed number and different type of alert generated by proposed model. Table V shows the top three alerts generated by proposed model for both Persons 1 and 2. Figure 7 represents the number of alerts generated each day by the proposed model.

Table IV. Number of alerts generated by proposed model.

	Proposed model	
	Person 1	Person 2
Average number of alert each day	11.4	13.1
Different alerts	10	10

Table V. Top three alerts generated by proposed model.

	Alert 1		Alert 2		Alert 3	
	Name	No.	Name	No.	Name	No.
Person 1	Switch off toilet light	33	Check Kitchen	27	Take medication	12
Person 2	Switch off kitchen light	36	Switch off toilet light	22	Microwave is ON	8

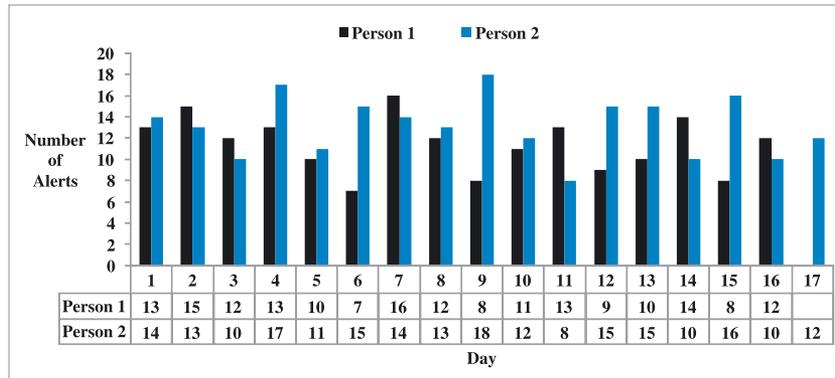


Figure 7. Number of alerts generated by proposed model each day.

### 5.2. Discussion of results

Proposed model provides SGN-based evaluation of smart home environment in which activities are recognized based on multiple ubiquitous sensors. Complete SGN graph is created dynamically, and Nash equilibrium is calculated using GamePlan Software from sensor data of two different homes. In this section, proposed model results are compared with Tapia *et al.* [60] results.

Proposed system identifies more number of activities as compared with Tapia *et al.* [60] as listed in Table I. Tapia *et al.* found activities based on Naïve Bayes classifier, which misses certain sensors from different location, whereas proposed model is completely dynamic and identifies activities based on all triggered sensors. For example, in sensor data of Person 1 on 4/1/2013 at 23:09:34, Tapia *et al.* [60] recognize it as toileting, whereas it was living room cabinet which proposed model identified correctly. Many similar cases are detected by proposed model. Hence, it results in increase number of activities identified and better results as shown in Table II and Figure 4.

Sequences of activities are identified in proposed model using complete SGN graphs for each day as shown in Table III. It is very important functionality provided by proposed model as compared with Tapia *et al.* [60]. Number of sequences are high when sequence size is three because single activity can have multiple triplet of sequences. However, when sequence size is set to five, number of sequences decreases to large extent, but these sequences are more accurate in representing the flow of activities as shown in Table III and Figure 5. As shown in Figure 5(a), increase in sequences of size three results in decrease in number of sequence with size five because in these days person is performing small activities containing less number of triggered sensors. As listed in Table III, Person 2 has less number of distinct sequences because Person 2 stayed more in house than Person 1 hence resulting in less variety of activities. Although for the same reason, numbers of sequences identified every day are high for Person 2 than Person 1.

Based on stored sequences of size five, activities of Week 2 are compared with activities of Week 1 to find certain set of fluctuations. Proposed model detected small set of fluctuations, as shown in Figure 6, which are very important for any smart environment.

Proposed model stored 10 alerts with some of sensor SGN's. Average number of alerts generated by Person 2 is higher than Person 1 because Person 2 stays more in the home. Table V shows top three alerts generated by proposed model which are consistent with activities performed by both the persons.

Results generated from experimental evaluation of proposed game theory-based decision-making in smart home environment of two separate homes prove its applicability and accuracy. Game theory combined with dynamic SGN was able to identify activities with more accuracy and better performance.

## 6. CONCLUSION

Each smart environments will have multiple sensors which will collaborate with each other to perform certain action. In this paper, SGN-based smart environment evaluation model is proposed. It uses

benefits of SPN and game theory to take dynamic actions in any smart environments. Key point of paper is formulation of mathematical foundation of SGNs for IoT-based smart environments. Simulation evaluation proved the applicability of proposed system. Future work will include the use of cost, energy consumption, and security in SGNs for IoT-based smart environments.

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## REFERENCES

1. That ‘Internet of Things’ Thing – RFID Journal. [Online]. Available: <http://www.rfidjournal.com/articles/view?4986>. [Accessed: 25-Jan-2016].
2. ITU Internet Reports 2005: The Internet of Things. [Online]. Available: <http://www.itu.int/osg/spu/publications/internetofthings/>. [Accessed: 25-Jan-2016].
3. Gubbi J, Buyya R, Marusic S, Palaniswami M. Internet of Things (IoT): a vision, architectural elements, and future directions. *Future Generation Computer Systems* 2013; **29**(7):1645–1660.
4. Perera C, Zaslavsky A, Christen P, Georgakopoulos D. Context aware computing for the Internet of Things: a survey. *IEEE Communication Surveys and Tutorials* 2014; **16**(1):414–454.
5. Xu B, Da Xu L, Cai H, Xie C, Hu J, Bu F. Ubiquitous data accessing method in iot-based information system for emergency medical services. *IEEE Transactions on Industrial Informatics* 2014; **10**(2):1578–1586.
6. Tarouco LMR, Bertholdo LM, Granville LZ, Arbiza LMR, Carbone F, Marotta M, de Santanna JJC. Internet of Things in healthcare: interoperability and security issues, in *2012 IEEE International Conference on Communications (ICC)*, 2012, pp. 6121–6125.
7. Bi Z, Xu LD, Wang C. Internet of Things for enterprise systems of modern manufacturing. *IEEE Transactions on Industrial Informatics* 2014; **10**(2):1537–1546.
8. Sauter T, Lobashov M. How to access factory floor information using internet technologies and gateways. *IEEE Transactions on Industrial Informatics* 2011; **7**(4):699–712.
9. Meyer CD, Plemmons RJ (Eds). *Linear Algebra, Markov Chains, and Queueing Models*, vol. **48**. Springer New York: New York, NY, 1993.
10. Hamdi M, Abie H. Game-based adaptive security in the Internet of Things for eHealth, in *2014 IEEE International Conference on Communications (ICC)*, 2014, pp. 920–925.
11. Kumar N, Chilamkurti N, Misra S. Bayesian coalition game for the Internet of Things: an ambient intelligence-based evaluation. *IEEE Communications Magazine* 2015; **53**(1):48–55.
12. Ding Y, Zhou X, Cheng Z, Lin F. A security differential game model for sensor networks in context of the Internet of Things. *Wireless Personal Communications* 2013; **72**(1):375–388.
13. Fang S, Zhu Y, Xu L, Zhang J, Zhou P, Luo K, Yang J. An integrated system for land resources supervision based on the IoT and cloud computing. *Enterprise Information Systems* 2015:1–17. DOI: 10.1080/17517575.2015.1086816.
14. Tai H, Celesti A, Fazio M, Villari M, Puliafito A, Dio C, Agata S. An integrated system for advanced water risk management based on cloud computing and IoT, in *2015 2nd World Symposium on Web Applications and Networking (WSWAN)*, 2015, pp. 1–7.
15. Sehgal VK, Patrick A, Soni A, Rajput L. *Intelligent Distributed Computing*, vol. **321**. Springer International Publishing: Cham, 2015.
16. Hao Q, Zhang F, Liu Z, Qin L. Design of chemical industrial park integrated information management platform based on cloud computing and IOT (The Internet of Things) technologies. *International Journal Smart Home* 2015; **9**(4):35–46.
17. Ouyang ZH, Ma JY. The measure platform for circular economy based on the cloud computing and IOT, in *Environment, Energy and Sustainable Development - Proceedings of the 2013 International Conference on Frontier of Energy and Environment Engineering, ICFEEE 2013*, 2014, vol. **2**, pp. 951–958.
18. Sun LN. Building intelligent parking lot based on RFID and cloud computing technology. *Advances in Materials Research* 2013; **846–847**:1550–1553.
19. HJ Ding. Traffic flow data collection and signal control system based on Internet of Things and cloud computing *Advance Mechatronics, Automation Application Information Technology Pts 1 2*, vol. **846–847**, pp. 1608–1611, Nov. 2014.
20. Jiang ZX, Chen YL, Chen JJ, Wu WT. An NFC-driven home automation framework: an integration of WSN, social networks and cloud computing in. *Frontiers in Artificial Intelligence and Applications* 2015; **274**:1489–1498.
21. Soliman M, Abiodun T, Hamouda T, Zhou J, Lung C-H. Smart home: integrating Internet of Things with web services and cloud computing, in *2013 IEEE 5th International Conference on Cloud Computing Technology and Science*, 2013, vol. **2**, pp. 317–320.
22. Wang C, Bi Z, Da Xu L. IoT and cloud computing in automation of assembly modeling systems. *IEEE Transactions on Industrial Informatics* May 2014; **10**(2):1426–1434.

23. Tao F, Cheng Y, Da Xu L, Zhang L, Li BH. CCIoT-CMfg: cloud computing and Internet of Things-based cloud manufacturing service system. *IEEE Transactions on Industrial Informatics* May 2014; **10**(2):1435–1442.
24. Mohammed J, Lung C-H, Ocneanu A, Thakral A, Jones C, Adler A. Internet of Things: remote patient monitoring using web services and cloud computing, in *2014 IEEE International Conference on Internet of Things (iThings), and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom)*, 2014, pp. 256–263.
25. Wang HZ, Lin GW, Wang JQ, Gao WL, Chen YF, Duan QL. Management of big data in the Internet of Things in agriculture based on cloud computing. *Applied Mechanics Materials* Apr. 2014; **548–549**:1438–1444.
26. Yu QD, Tian YC, Hua XF. The establishment of agricultural information service model under the Internet of Things and cloud computing environment. *Applied Mechanics Materials* Nov. 2014; **687–691**:1966–1969.
27. Chen L, Hu Y, Zhang F, Duan W, Yu P. Performance improving design on cloud computing for agricultural products safety traceability system. *Nongye Gongcheng Xuebao/Transactions Chinese Soc. Agric. Eng.* 2013; **29**(24):268–274.
28. Le Vinh T, Bouzeffrane S, Farinone J-M, Attar A, Kennedy BP. Middleware to integrate mobile devices, sensors and cloud computing. *Procedia Computer Science* 2015; **52**(1):234–243.
29. Botta A, de Donato W, Persico V, Pescapé A. Integration of cloud computing and Internet of Things: a survey, *Futur. Gener. Comput. Syst.*, Oct. 2015.
30. Botta A, de Donato W, Persico V, Pescapé A. On the integration of cloud computing and Internet of Things, in *2014 International Conference on Future Internet of Things and Cloud*, 2014, pp. 23–30.
31. Yannuzzi M, Milito R, Serral-Gracia R, Montero D, Nemirovsky M. Key ingredients in an IoT recipe: fog computing, cloud computing, and more fog computing, in *2014 IEEE 19th International Workshop on Computer Aided Modeling and Design of Communication Links and Networks (CAMAD)*, 2014, pp. 325–329.
32. Aazam M, Khan I, Alsaffar AA, Huh E-N. Cloud of Things: Integrating Internet of Things and cloud computing and the issues involved, in *Proceedings of 2014 11th International Bhurban Conference on Applied Sciences & Technology (IBCAST) Islamabad, Pakistan, 14th - 18th January, 2014*, 2014, pp. 414–419.
33. Shon T, Cho J, Han K, Choi H. Toward advanced mobile cloud computing for the Internet of Things: current issues and future direction. *Mobile Networks Applied* Jun. 2014; **19**(3):404–413.
34. Suciú G, Halunga S, Vulpe A, Suciú V. Generic platform for IoT and cloud computing interoperability study, in *International Symposium on Signals, Circuits and Systems ISSCS2013*, 2013, pp. 1–4.
35. Renner T, Kliem A, Kao O. The device cloud – applying cloud computing concepts to the Internet of Things, in *Ubiquitous Intelligence and Computing, 2014 IEEE 11th International Conference on*, 2014, pp. 396–401.
36. Dai W, Jin H, Zou D, Xu S, Zheng W, Shi L, Yang LT. TEE: A virtual DRTM based execution environment for secure cloud-end computing. *Future Generation Computer Systems* Aug. 2015; **49**:47–57.
37. Shaoling S, Jing Z, Moliang C, Hui R, Yi C, Xiaodong F. Network energy consumption analysis and dormancy mechanism based on ant colony algorithm in cloud computing environment for IOT service and real-time embedded industrial control system, in *The 27th Chinese Control and Decision Conference (2015 CCDC)*, 2015, pp. 5588–5592.
38. Villari M, Celesti A, Fazio M, Puliafito A. *Internet of Things. IoT Infrastructures*, vol. 151. Springer International Publishing: Cham, 2015.
39. Amato A, Di Martino B, Venticinque S. Big data processing for pervasive environment in cloud computing, in *2014 International Conference on Intelligent Networking and Collaborative Systems*, 2014, pp. 598–603.
40. Li K, Tang X, Li K. Energy-efficient stochastic task scheduling on heterogeneous computing systems. *IEEE Transactions on Parallel and Distributed Systems* Nov. 2014; **25**(11):2867–2876.
41. Mei J, Li K, Li K. A resource-aware scheduling algorithm with reduced task duplication on heterogeneous computing systems. *Journal of Supercomputing* Jan. 2014; **68**(3):1347–1377.
42. Kang J, Yin S, Meng W. *Proceedings of International Conference on Computer Science and Information Technology*, vol. **255**. Springer India: New Delhi, 2014.
43. Jiang L, Da Xu L, Cai H, Jiang Z, Bu F, Xu B. An IoT-oriented data storage framework in cloud computing platform. *IEEE Transactions on Industrial Informatics* May 2014; **10**(2):1443–1451.
44. Da-wei LI, Geng Y. Repeated game based secret sharing scheme in IOT, *Journal on Communications*, vol. 31, no. 60873231. *Journal on Communications*, 31(9 A), pp 97-103, 2010, pp. 97–103, 2010.
45. Hu HY, Li ZJ, Hu H. Joint resource allocation based on bidding and credibility in Internet of Things. *Tongxin Xuebao/Journal Commun.* 2011; **32**(9 A):251–262.
46. Tang X, Li K, Liao G, Fang K, Wu F. A stochastic scheduling algorithm for precedence constrained tasks on grid. *Future Generation Computer Systems* 2011; **27**(8):1083–1091.
47. Liu W, Fang B, Yin L, Yu X. Detection of misbehaving nodes in malicious organization dominant networks in Internet of Things. *Journal Conver. Information Technology* 2012; **7**(17):223–231.
48. Lan HY, Song HT, Liu HB, Zhang GY. Heterogeneous-oriented resource allocation method in Internet of Things. *Applied Mechanics Materials* 2013; **427–429**:2791–2794.
49. Wang H, Li Y, Mi M, Wang P. Secure data fusion method based on supervisory mechanism for industrial Internet of Things. *Yi Qi Yi Biao Xue Bao/Chinese Journal of Scientific Instruments* 2013; **34**(4):817–824.
50. Fuhong L, Qian L, Xianwei Z, Yueyun C, Daochao H. Cooperative differential game for model energy-bandwidth efficiency tradeoff in the Internet of Things. *China Commun.* 2014; **11**(1):92–102.
51. Zuo J. Repeated game theory intrusion detection model for the Internet of Things. *Chongqing Daxue Xuebao/Journal Chongqing University* 2014; **37**(6):90–96.

52. Liu Y, Chen Z, Lv X, Han F. Multiple layer design for mass data transmission against channel congestion in IoT. *International Journal of Communication Systems* 2014; **27**(8):1126–1146.
53. Li K, Liu C, Li K. An approximation algorithm based on game theory for scheduling simple linear deteriorating jobs. *Theoretical Computer Science* 2014; **543**:46–51.
54. Liu C, Li K, Xu C, Li K. Strategy configurations of multiple users competition for cloud service reservation. *IEEE Transactions on Parallel and Distributed Systems* 2016; **27**(2):508–520.
55. Lv X, Zhang R. Profits distribution of operators led Internet of Things industrial value chain based on game theory. *Advances in Information Sciences and Service Sciences* 2012; **4**(23):55–62.
56. Lv X, Zhang R, Jiang Y. Competition and cooperation between participants of the Internet of Things industry value chain. *Advances in Information Sciences and Service Sciences* 2012; **4**(11):406–412.
57. Li W, Mei L, Nie K. Research on choices of methods of Internet of Things pricing based on variation of perceived value of service. *Journal Industrial Engineering Management* 2013; **6**(1):175–187.
58. Zhang Q. A multi-agent simulation model combined with evolutionary game for cooperative patterns of IOT. *Journal of Information and Computing Science* 2013; **10**(10):2933–2942.
59. Qi K, Bi ML. Evolutionary game research on the core business and consumer behavior in green supply chain under IOT environment. *Applied Mechanisms Materials* 2014; **678**:697–704.
60. Tapia EM, Intille SS, Larson K. Activity recognition in the home using simple and ubiquitous sensors. *Pervasive Computational* 2004; **3001**:158–175.
61. Software reviews. *The Economic Journal* 2000; **110**(461):166–186.