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Enhancing Supply Chain Management in Healthcare Facilities in Ghana: An Overview

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ABSTRACT

Contemporary healthcare institutions have come to realized that making prudent decisions is very critical in their resolve to reducing costs in the health care supply chain management. These prudent decisions will inure to the benefit of the healthcare sector by curtailing operational bottlenecks while still maintaining processes efficiency and timely delivery. SCM in healthcare with respect to the products availability and accessibility to patients is of a great concern since it's premised on life or death. In this regard, there is a strong conviction to always get it right in this all important sector. Simulation Modelling has been used in diverse fields especially in engineering. By adopting Simulation and Modelling (SM) as a new approach in the healthcare sector, solutions and support decisions owing to diverse SCM problems could be tested by supply chain managers. In this paper, we make a case to analyze past Simulation and Modelling (SM) situations that support SCM decision making in healthcare. Key challenges pertaining to SCM modelling are also identified. Key contemporary technologies that meet the challenges in healthcare SCM are also explored.

Keywords: supply chain, simulation, modelling, healthcare, decision

INTRODUCTION

Contemporary technological innovations infused in the healthcare management systems have undoubtedly brought sigh of relief in healthcare organizations day-to-day operations (Faulkner 2008; Vincent et al. 2016). Specifically, through sustained technological solutions Supply Chain (SC) operations have seen major improvement. With that notwithstanding, there is still more work to be done to further enhance the operations and performance with sole intention to minimize cost. Over the years, there have been many variations of SC management models introduced in the healthcare environment (Dobrzykowski et al. 2014) ; however it has not yielded much result.

Developers and users have operationalized Simulation Modelling (SM) in various field of expertise to assess their mode of operations with varied possible alternative conditions. This has helped achieve optimum operating conditions providing users the requisite tools to exploring myriad alternatives by altering different methods and conditions without obstructing the foundational operational systems. This has compelled managers to introduce SM to the SCM in healthcare delivery system. Supply Chain Management (SCM) with its several parameters and requirements, has become very critical for management and operational staff to be conscious of possible outcome in case of any alteration to work conditions or parameters (Altaher et al.). Equipping users' with the right kind of SM tools could better serve the needs of healthcare providers (Motola et al. 2013). Being equipped with the right SM tools could assist users explore best available distribution/scheduling channels that satisfy healthcare providers'. This subject matter and models with accompanying tools were carved out for specific types of SC requirements in the healthcare sector. In this study, the researchers take a cursory look at already existing SM that supports decision making in healthcare SCM. We also touch on some key challenges that militate against SM efforts in healthcare SCM, and expound on new emerging technologies that meet these SM challenges.

Background and Related Work

The healthcare industry is witnessing a prevalent rise in competition (Handa et al. 2012). Healthcare providers' face the challenge of minimizing operational while improving the quality of healthcare services to patients in order to be competitive (Attaran 2012; Devaraj et al. 2013; Mohammad Mosadeghrad 2013). For example, stakeholders' are incensed as SCM cost is estimated at 50 percent being the hospital's operating budget after labor cost (Shretta et al. 2015). Healthcare SCM is the process of delivering the right products in the right quantities to the right patient care locations and at the right time with satisfying service levels and minimized system-wide costs (Almaktoom et al. 2016; Polater et al. 2014). Although SCM is complex, dynamic; it is fraught with uncertainty and high variability (Roh et al. 2014; Srinivasan et al. 2011); this is because SCM encompasses integrated and interrelated activities undertaken by various stakeholders (i.e., consumers, suppliers and distributors). It is estimated that, a well and efficiently managed healthcare supply chain falls between 2 to 12 percent of total hospital operating cost (Haszlinna Mustaffa et al. 2009; Ranganathan et al. 2004).

Managing SC is premised on prudent decision making with a holistic perspective governing all elements that affect SCM process (Cruz 2009; S. Tsanos et al. 2014). Certainly, SC managers in various healthcare sectors need to have clear understanding relating to their SCM processes to better appreciate the causes of uncertainty and a possible impact on these processes. In case of unpredictable situations, SC managers need to make accurate projections while adjusting plans in real time (Samvedi et al. 2012). Moreover, they need to investigate and validate solutions for different types of SCM challenges. SC managers' concerted effort to ensure products availability and accessibility to patients is welcoming since it has to do with life and death. By providing effective solutions that supports decision making, risk management, and cost effectiveness analysis associated with healthcare SCM, we suggest Simulation Modeling (SM).

Simulation refers to imitating the operations and a process of a system in the real world (Robinson et al. 2012); while modeling is the process of understanding and describing the behavior of a system (Rebuge et al. 2012). SM technology is used in analyzing and evaluating logical scenarios with regard to real world systems to predict its performance and outcomes after potential changes to the system. This suggests that SM tools can assist stakeholders in analyzing and predicting ultimate effects inherent in the current system or as a design tool to forecast the performance of new system under varied set of condition (Agyapong-Kodua et al. 2009; Palmer et al. 2010). In principle SM can help reduce needless human intervention, reduces cost, and risks in case such experiments occur in reality (Cox 2013). Further, continued engagement in SM development paves way for concerned stakeholders to have in-depth insight into the problems that are needed to be tackled. This helps them build new perspectives in relation to the system's elements of interest and the measures of its performance (Bhattacharjee et al. 2014; Mielczarek et al. 2012). A lot of studies (Kinder et al. 2014; Ponis et al. 2014) have highlighted the unique role of SM in SCM and its prospects of improving decision making in SC context.

They discussed the benefits of using SM in analyzing and evaluating SCs, process control, decision support, and proactive planning. They made a case that support SM as a powerful tool for acquiring understanding into SCM. Overall, the benefits of SM in SCM include but not limited to the following: understanding overall SCM processes and characteristics; capturing dynamics of SCM; modeling unexpected events and understanding their impact on SC in the planning process. Accordingly, it is critical to have of the benefits of SM in SCM optimization and what are the current issues and challenges in the field.

SM Tools to Support Decisions Making in SCM

Many research works have been undertaken to develop SM tools to support decisions making in SCM. To buttress this point, we briefly cite some examples of this work. Biswas et al. (2005) developed "DESSCOM" as cited by Zhang et al. (2014): a decision support for supply chains through object modeling, which enables strategic, tactical, and operational decision making in SCs. Ding et al. (2006)also introduced a simulation and optimization tool "One" to support decision during assessment, design, and development of supply chain networks as cited (Nguyen et al. 2014). Blackhurst et al. (2005) developed a decision support system, "PCDM," for different decisions within the supply chain networks as cited by (Bode et al. 2015). In Melouk et al. (2013), the researchers used SM technique to develop a decision support system to model manufacturing systems and to evaluate design alternatives. Yücesan et al. () developed a specialized and domain oriented decision support tool "DST-SC" that is easy to be used by non-experts in simulation as cited by (Esmail et al. 2016). DST-SC is also featured by its high degree of flexibility in modeling SC functions and its ability to handle large complex problems. The use of SM in health has been very slow compared to other sectors, but it is rising steadily (Brailsford et al.

2004). A lot of studies (Brailsford et al. 2009; Jahangirian et al. 2010) have explored the value of SM to support decision making in healthcare SCM in relation to other industries. Many studies have inspired the development SM tools that have help resolved the problems inherent in healthcare SCM. For instance, (Lapierre et al. 2007) tackled the problem of logistics and inventory replenishment through coordinating the procurement and distribution operations while valuing inventory capacities. Researchers (Ghandforoush et al. 2010; Van Dijk et al. 2009) addressed the optimization problem of production and inventory management of blood supplies.

Tebbens et al. (2010) posited the relationship between vaccine supply and vaccine demand to calculate pediatric vaccine stock levels necessary for avoiding interruptions in vaccination schedules for children. Again, (Belciug et al. 2016; Postacchini et al. 2016) outlined the optimal inventory policies for an inpatient hospital pharmacy with enhancement in cost performance. da Silva et al. (2006) established a decision support system based on integer-programming models to douse the problem of acquisition and allocation of medical materials. Lastly, (Baesler et al. 2014; Stanger et al. 2012) developed a SM tool to analyze the supply chain of blood and blood products. They revealed that decision makers or stakeholders can use their expertise and experiences which is as a result of SM to make informed and less risky decisions with respect to changes in SC. Their conclusion suggested that SM has boosted the overall quality of healthcare by allowing better allocation of scarce resources

Healthcare SC Design and Management

Due to the complexity of SCM, there is a magnifier effect on the problem with the healthcare industry in the spotlight. Healthcare SCM ensures a high service level by maximizing the allocation of resources to respond effectively and promptly to the patient care needs. Moreover, patients' lives are promptly impacted rather than their livelihood. Therefore, there is a clear disparity between healthcare SCM and SCM in other jurisdictions as it takes care of a plethora of items in varying quantities in response to the large number of diagnosis types and methods. This is controlled by diverse legislations and the important role played by healthcare professionals (Krause et al. 2009; Rego et al. 2009). In as much as patients are direct consumers of products supplied through SC, they have no upper hand on how these products are selected. In sharp contrast to other sectors, expired products are destroyed when it cannot be auctioned or sold directly. In addition, the ever changing nature of technologies in the healthcare sector result in short product life span and cost of procuring healthcare professional preference items. In conclusion, it throws a major challenge on planners in healthcare SCM to accurately predict the frequency, duration, and diagnosis types for patient episodes and accordingly the associated product demands.

Healthcare SCM facilitates patients' care by infusing varying medical professionals with products and services they need to deliver prompt and best quality medical care. Additionally, both patients and medical professionals come with diverse needs. Much effort is needed to better address these challenges while satisfying customers' peculiar requests.

In the same vein, SCM promote the strategic vision of healthcare organizations in order to maximize patient care and minimize cost. By ensuring product availability, minimizing storage space (to maximize patient care space), lowering material handling time and cost, and minimizing non-liquid assets can be brought into fruition. Therefore, decision making processes in healthcare SCM must take into consideration many parameters such as cost, profitability, standardization, and inventory management. Contemporary practice healthcare SCM as depicted below (Figure 1) is divided into a series of cycles each perform at the interface among various successive stages.

(i) Customer order is triggered when a product's level reaches a certain low level as it is consumed through usage and sales.
(ii) Forecasting and product need verification verify the need to order new stock based on usage and sales in addition to prevailing trends, product availability, on hand stock and product cost.
(iii) Product selection and procurement: used to select the appropriate product to order based on availability, cost verification, order quantity, lead time and delivery date.
(iv) Receive, store, and distribute: verify ordered products based on approval.
(v) Budget, inventory management, and cost containment: depicts SC fiscal proposition to the organization as general policies and budget concerns are addressed and orders are optimized to meet overall organizational goals.

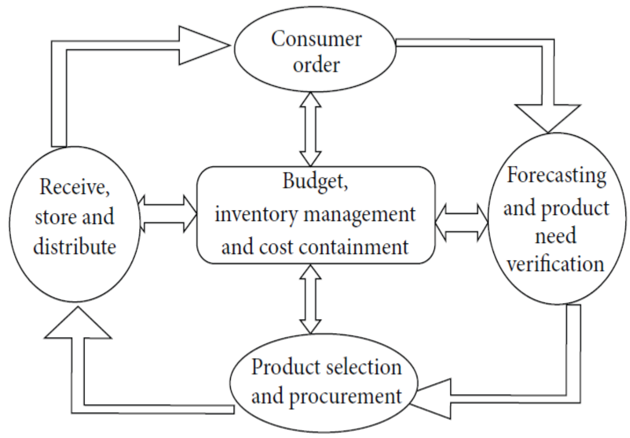

Figure 1: Modern Supply Chain Management Process

Illustrated in the figure above is a typical SC process. However, the focus on consumer is being ignored while cost to revenue approach takes centre stage. Putting this into critical perspective, winning SC managers find their competitive edge by drawing a balance between the idea of meeting consumers' demands and fiscal responsibility. Effective healthcare SC management ply on unalloyed performance which represents a balanced approach including: total cycle time; product availability; quality; responsiveness; compatibility with policies and guidelines; flexibility; and cost effectiveness (Igwe 2016). Effort to attain SCM goals within high performance measures hinges on management principles (tactical, strategic etc). Strategic decisions primarily deals with SC structure. Planning narrows the gap between strategic decisions and operational decisions with regards to the day-to-day functions (Deverell 2012; Tufinio et al. 2013).

Strategic Decision Making: The price elasticity of demand in the SCM process cannot be over emphasized. There are a plethora of products available to end users whose functions cuts across the healthcare SC. The real issue confronting stakeholders is getting to order the products that give value for money and at the same time satisfying the needs of the majority. Inventory is an asset in every industry and the healthcare industry is no exception. To ensure a clear balance of cost the operational workflow inventory must be sustained. In dealing with organizations with many consumers (healthcare professionals) painstaking decisions have to be made with regard to individual's product preferences based on their own reasons.
Packaging standardized products that meet the expectation and needs of all engaged in optimized inventory levels is a hard and critical decision for SC managers to make. Deciding where to site warehouse facilities poses another challenge to SCM decision makers.

Planning Decision Making: To put consumer needs and the organization's goals on equal terms, the consumer's input becomes imperative at the time organization's needs to decide the best fit in the quest to meet financial aspirations. As depicted in Figure 1, the consumer is taken out of the center and replaced with three necessary elements that are the core foundation for planning today's healthcare SC and for customers/suppliers' relationships. Identifying where profitability and sustainability will occur make it easier for SC to focus on the products necessary to provide the needed services. Budget constraints lead healthcare SC managers to put together new functions and policies into their procurement, inventory managements and distribution cycles.

Operational Decision Making: The main challenge confronting healthcare SCM in terms of operations is maintaining efficient and adequate inventory levels whiles ensuring quality and timely patient care. In addition, there is wastage (i.e. too much inventory which leads to high product expiry rates). There are various factors that healthcare organizations are challenged with: wastage due to poor planning, not understanding appropriate inventory levels, and ineffective monitoring budgetary guidelines. SC departments need to be innovative in their bid to keep consumers' happy. However, too much of a good thing can create a snowball effect and end up costing the organization heavily. Inventory can serve as potential source of revenue. Having an overstock (wastage) of inventory adds to organizations opportunity costs; money that would have otherwise been spent elsewhere within the organization. Since a considerable amount of inventory is moved each day in the healthcare environment, it has become appropriate to maintain n necessary stock levels of those products, with a number of them quite costly. The operational challenge for healthcare SC is finding and maintaining sanity in the inventory setup so hospital budgetary requirements and consumer demands are realized.

Proposed Simulation Models

What-if analysis tools infused together with Simulation models can help in shaping the design and management of health care SC. With respect to SC design issues, SM can support decisions concerning process flows, localization (location of facilities, distribution systems), selection (suppliers, partners, products), and size (capacity of facilities). Owing to SCM challenges, SM can help make decisions concerned with policies, planning processes, inventory management, and suppliers/consumers collaboration agreements. In this paper, we present a number of proposed modeling efforts that aids decision making processes in healthcare SCM. We emphasize on the key indices of SCM: scope, problem, decision variables, objective, monetary value, customer service initiatives, and constraints. Various decision parameters aim to limit the broad decision objectives in SC and to gauge its performance according to the set objectives. The monetary value reflects the cost efficiency and profitability of SCM activities while the customer service initiatives include the two main elements for consumer satisfaction: product availability and response time. Constraints represent restrictions placed on SC, which are generally pertaining capacity, service compliance, and the balance between demand and consumption. Proposition tabled by the modelers during model development to simplify the reality of SC are also addressed in our discussion.

Optimizing Scarce Drug Allocation: SM based decision support system (DSS) has been instituted to support the Drug Distribution Channel in Ghana which is regulated by the Ministry of Health (MoH). DDC aimed to manage fair and equitable scarce drugs distribution in the regions with the involvement of 150 clinics and 25 pharmaceutical companies involving 125 drugs in 20 drug categories. The allocation problem as described was nonlinear, multi-objective, and large in size. Therefore, the proposed DSS utilized a multi-objective optimization model and a heuristic solution to accomplish optimized distribution while taking into account efficiency, effectiveness, and equity of the drug-allocation process.

Allocation efficiency in the model was measured by the extent to which all drugs are distributed to clinics with a maximum dollar value of drugs allocated (equal to a minimum left over budget) in a given ordering period. Premised on effectiveness we measured the extent to which drugs need by clinics were allocated and received. We use weight matrix to establish the critical role of drugs for various clinics. To ensure equity, the model adopted allocation heuristic approach to get each clinic fraction that is weighted by and proportional to the ordered amount of any short supply drug. Critical decision variables use the dollar value of drug received by a clinic and the binary state (0 or 1) represents if a clinic received any allocation of drug or not.

Looking at the performance indices, the model points out two objective functions: (1) minimize the leftover budget in any given period (to achieve efficiency) and (2) minimize the difference between allocation ratios and weighted orders from clinics (to achieve effectiveness and equity). The model was set to perform according to several constraints as follows.

(i) Clinic constraints: clinics are not expected to spend beyond their allocated budget threshold in ordering drugs.

(ii) Pharmaceutical firm constraints: Cedi value term of total disbursement should not exceed the limits in the settlement agreement.

This model solution was instituted to identify scarce medicines whiles looking at a fair and balanced allocation among clinics considering all possible alternatives. The performance of the allocation heuristics greatly hinges on the priority provided by the decision makers through the weight matrix.

The proposed DSS in this work was proven successful at providing efficient, effective, and fair methods to allocate scarce drugs. On the contrary, the primary assumptions did not consider procurement centers for different clinics in one region. Orders from such facilities tend to overshadow other clinics. In as much as the model was augmented by normalizing the base weights for all large clinics, there is still an issue with the model scalability and complexity. The large size of the weight matrix increases the complexity of priority weight determination. Finally, this model is specific to DDP with no immediate applicability elsewhere.

Optimizing Drug Inventory. Brako *et al. (2016)* postulated another modeling approach for inventory and ordering policies for drugs for inpatient hospital pharmacies. The motivating factor is to minimize waste and holding cost while maximizing prompt access to the drugs. The approach made use of patients' medical condition information to underline the necessary inventory level of raw materials and finished pharmaceutical drugs.

Markov decision process (MDP) was used to model the drug demands as a function of patient condition and accordingly to decide the appropriate level of drug inventory and the drug order quantities. The objective functions were to (1) minimize all associated costs including stock-out cost for both finished and raw goods and inventory expiry cost and (2) maximize timely access to the required drugs. The main assumption was that there was no back-logging of demand. The patient demand was assumed to be fulfilled at the same day even if it involves procuring the drug from a different hospital. The model also assumed that out-of-stock goods are received immediately after order placement, while raw materials have one period delay. State definition in the corresponding MDP involved two components.

(i) Patients: two types of patients are modeled by two distributions of corresponding mean values to reflect high and low demand variability. A third type of patients is defined to represent patient discharge (absorbing state). For example, a patient with severe condition will be of type 1 with a higher mean of demands. The unique patient demands (Q) were modeled as discrete nonnegative values based on stationary probability mass function. The maximum demand was assumed to be a finite number. The demand's mean decreases from patient type 1 to 3.

(ii) Inventory is defined as a multidimensional vector (I) to meet the assumption of two drug forms: raw and finished.

The model espouse on transition probabilities which captures variety of changes that occur in patient classification from one type to another with some alterations in demand as well. Rate of arrival was dependent on type of patient. Patients' demands was determining factor with respect to how much drug quantity and raw material units to order. This happens at a given period of time where system state (I, Q) was obtained in evaluating decisions.

Backward recursion was adopted to optimally and numerically determine the inventory policy. Eventually, the outcome suggested optimal policy has a base stock structure of which base stock levels are dependent on the raw and processed goods as well as the patient types mix. Precisely, two policies were put together and compared: adaptive policy (AP) that is based on the MDP solution and fixed policy (FP) that uses a fixed base stock level. In the defined multi-scenario experiment set, AP outperformed FP.

The model does not take into cognizance the production cost that may concern some impatient pharmacy environments. Healthcare SCM have no hold of production costs; but, fore-knowledge of products can aid in negotiating effective pricing. Moving on, it is not ideal to tie the patient type to the demand variability. Patients' discharged higher number of drugs may exceed wards that may be needed.

These concerns may bear semblance with the worldwide shortage of the drug that may impact order quantity, impulse increase in demands, and the drug availability from other storage facilities. One day delay for the delivery of raw materials can be a strong proposition to point out. This assumption arises since it requires having an idea of how much suppliers usually keep on hand to ensure these materials availability.

4.3. Optimizing All Products Inventory. Towards a more general solution regarding inventory optimization; (Duan et al. 2013; Kelle et al. 2012) came up with programming optimization model to determine the optimal general stock levels of products in hospitals controlled by space, delivery, and criticality of the products. The system being proposed has the sole aim of meeting healthcare SCM requirements. These among other things include achieving high service levels with lower delivery overheads, making sure that materials are not overstocked; supplying all needed products with no delay or no out-of-stock problems; and reducing the cost of stock hold and distribution. As a result, this model is premised on three decision variables that were associated with each product to be stored:

(1) Service level (initially set between 90% and 99%); (2) frequency of delivery (initially set between daily to once every ten days); and (3) stock-up amount. The objective functions were set to (1) maximize the minimum service level and (2) maximize the average service level. The model approached the problem as a type of "unbounded knapsack problem" with the knapsack being the stock hold in this case. Getting to know the maximum value to be placed in the knapsack within the weight constraint remains the real antidote. The weight constraint runs in parallel to the inventory volume to control the amount of each product to be stored. There is a school of thought that product demand is evenly distributed. The constraints set in this model include the following:

Inventory constraint: to ensure that the relationship between the decision variables is kept consistent.

(i) Space constraint: to ensure that the volume of all products of different types to be stocked up is less than the maximum available space.

(ii) Criticality constraint: to allow consumers to impose constraints to f ix any product to the highest level of 99%.

This model was operationalized using OPL (optimization programming language) to generate an optimal inventory policy to achieve the best probable solution that has many products of high importance at high service level. The model was experimented within a real time setting in two different sets. The first set of experiments was intended to track how varying the decision variables results in various optimal policies; while the second set was intended to explore how different objective functions and search strategies improve the quality of the inventory policy. For these trials, the model was able to quantify and predict the inventory policy and how it behaves in the response to the changes in space and delivery pattern.

This proposed work is premised on the availability of product storage space in hospital sites based on the idea that products are supplied with regular (normally distributed) demands. On the contrary, products do assume highly dynamic and uncertain patterns in terms of demand needed at the hospital.

Any model to determine the optimal stock level in hospitals should realize (or predict) changes to demands and take action to adjust policies or supplies accordingly.

Optimizing Sterilization Logistics. In other SCM design, (Albers et al. 2015)revealed the problem associated with the logistics process optimization in SCM is by making known the potential model to optimize the flow of sterile instruments. Flow of sterilized items takes place between the central sterilization service department (CSSD) and the operation theatres (OT) in hospitals. In reality, the demand and consumption of sterilized items are determined by the number of planned and emergency surgeries. Sterile instruments are consumed in nets rather than individual items. Normally, sterile net includes items needed for a particular surgery. An effective logistic control principle applies to replenish immediately all items to the sterile storage area in OT and to process used items and return them to the storage area before the end of the day. Since the CSSD is mostly located near the OT the process takes more than a day. Nonetheless, this underlining principle is not enough as it requires maximum storage capacity in a critical area like the OT where space is more critical for patient care. Secondly, it requires additional working hours by CSSD for products that may not be needed by the next day; and lastly it adds unnecessary transportation overhead.

The model optimizes the logistic process by altering the afore-described principle and redesigning the process to improve product availability and reduce cost at the same time. Assumptions were made concerning outsourcing and he sterile nets only once a day with replenishment process completed on weekly basis involving three costs – transportation cost, OT storage cost, and instrument usage cost. The proposed model addresses two problem formulation settings.

(i) Deterministic optimization: sterile products can be delivered timely before surgery begins with the assumption that all surgeries and resulting sterile instrument net usage are predictable. The objective function resulting from this model requires minimizing the total cost by minimizing the number of transportation delivery for a given OT schedule considering the storage capacity at the OT.

To achieve this, the model was set to select a set of delivery moments for sterile nets that serve the largest number of surgeries scheduled in blocks. T he underlying assumption was that sterile nets were used in the block directly after delivery; that is, they did not need storage.

(ii) Nondeterministic optimization: this approach disposes the assumption that the OT schedule is predictable and solves the problem with the assumption that the number of required nets is unknown. Basically, the only way to deal with unplanned usage of sterile nets is by keeping and replenishing a safety sock. Accordingly, the system proposed four strategies.

(1) Arrange for sufficient safety stock in advance. This strategy deals with stochastic demands in a static manner and does not require information exchange on unexpected use.

(2) Include both planned usage as well as safety stock in the original planning. This strategy uses prior knowledge and does not require information exchange on expected usage.

(3) Schedule delivery only for planned usage; and guard against unplanned usage by an initial safety stock. When stock level drops below the safety stock level, the transportation plan is dynamically re-optimized based on real time information to include replenishment of nets which are below the safety stock level.

(4) Schedule delivery for both planned and expected usages; and guard against unplanned usage with an initial safety stock. The transportation plan is dynamically re-optimized

based on real time information to include replenishment of nets which go below safety stock levels. This strategy depends on prior knowledge and real time information.

The optimal delivery schedule forecast in all cases is computed using a dynamic programming approach. Proposed strategic solutions were compared against reference cost in a simulation environment. Policies with stochastic demands resulted in lower cost than the reference cost. The practical and theoretical work presented in this work shows that up to 20% cost reduction is possible through the optimization of the flow of sterile instruments between sterilization departments and hospital OTs along with processes' streamlining and materials' standardization. However, the transportation cost increases when outsourcing CSSD, which is balanced by the OT storage cost decrease. This would happen only if it is not possible to increase the storage capacity of the OT to handle weekly supplies of nets. In turn, this requires considering alternative solutions such as cheaper remote CSSD, cheaper intermediate storage areas near the OTs, or other solutions to counterbalance the increase in transportation cost.

Optimizing SCM Logistics: Silva et al. (2008), in their work also dealt with logistics process optimization which emphasized on redesigning the whole configuration of the hospital SCM. The major challenge with regards to the current SC configuration hinges on the lack of coordination between the strategic decision level and operational decision level. This intensifies the challenges with respect to the decision making processes in whether, when and how to utilize the existing SC structure. For instance, decision about storage centers location, how to use these locations for existing facilities, transporting materials between centers, and how to assign people to cover these centers. The main of this proposed model was to better advance the logistics organization of SCM services in the hospital to improve quality of service and lower overall cost, response time, and storage space. This model, rooted on Graph Theory describes multistage, multilevel and multiproduct production and distribution planning system. The model represented the multi-period dimension of the problem through replication of SC with inventory edges connecting storage areas in subsequent periods. Decision variables relate the quantities supplied to the supply path (edge). Therefore, moving a given inventory through one edge depends on the channel of supply the quantity of items has traveled before. The objective function is to cut down total cost which includes acquisition, transportation, administration and inventory carrying costs. The model presumed administrative cost is fixed while storage constraint is constant throughout the planning process. The model performs under the constraints below:

(i) demand satisfaction
(ii) flow persistence between SC members (represented by nodes in the graph),
(iii) storage capacity,
(iv) Aggregating all items
(v) producers supply capacity affecting all potential buyers
(vi) Non-negativity and integrality of decision variables.

The solution of the model involved selecting travelling paths with the minimum cost to distribute inventory. Given the combinatorial nature of the addressed problem and the size of instances involved, the approach developed to solve this model which adopted a hybrid algorithm based on meta-heuristic technique, Tabu Search (TS), and Variable Neighborhood Search (VNS). The solution suggested three-neighborhood structure (NS) for path completion or path substitution while delivering a certain quantity.

(i) Select paths with minimum cost, ignoring the current solution structure (other paths of current solution may use common edges of the under analysis path).
(ii) Select paths with minimum cost considering the current solution structure.
(iii) Select a new path by randomly choosing the chain elements while satisfying the capacity constraints.

Demand was described using normal distribution to represent units of high and low demand. According to the NS used, varied cost values was returned based on the attained solutions. Selecting the best alternative course of action depends on SC mangers to do critical assessment of how reasonable these solutions are. The preliminary computational results of the model portray the potentials of the approach in solving large scale and diversified SC configuration problems. Even though the approach does not consider sudden increases in the demand, it may be incorporated in a DSS to simulate, discuss, and negotiate SC coordination partnerships between neighboring hospitals and other members such as suppliers. On the other hand, the flexibility of the proposed method allows its application to SCs with diverse topologies and uncommon cost characteristics. On the contrary, all of these potentials are assessed with real data obtained from a real hospital SC.

Optimizing Logistics Activities: Contrary to the previous two models, Pan et al. (2007)tackled the problem of logistics optimization which is schedule oriented rather than an inventory-oriented approach. An inventory-oriented approach focuses on assuring sufficient inventory levels but does not account for human resources activities. In spite of these, SC managers in healthcare need answers to various questions that transcend inventory control such as those related to planning and control or scheduling of activities and manpower resources. Examples of these questions are when each employee should work? How often and when to replenish/visit each care unit (CU)? How often and when to call suppliers? Additionally, decisions bothering on inventory-oriented approach situate on cost or service levels and do not account for other beneficial aspects as attached to activities control.

Manpower resources in the hospital SCM are required to accomplish four main activities: (1) procurement and purchasing, (2) reception and handling, (3) replenishment preparation, and (4) distribution and inventory control at CUs. The proposed model aimed to support the optimization of the SCM through presenting a solution to schedule and coordinate these activities while respecting inventory cost and capacities. The presented solution is based on two modeling approaches that account for the many scheduling decisions concerning the SC managers.

The proposed model was designed to decide: (1) when each CU will be visited and which products will be delivered in each visit; (2) when each supplier will deliver to the hospital, and which products are included in each delivery; and (3) what inventory quantity is shipped directly to CU on the same reception day. Direct shipments to CUs require prompt delivery time, however it may demand more time as it may lead to more frequent purchases. Ultimately, three decision variables were identified with regard to the service sequence at a given period: suppliers' delivery, CU visits, and manpower time. To simplify the problem, assumption is made that only three large suppliers can visit the hospital several times a week while there is a total of 43 products to be delivered to 23 CUs by the three suppliers. For the testing purposes, only datasets of 10 and 20 products were used and the storage capacities of CUs were reduced accordingly.

The model included two types. The first type (M1) was an inventory cost-oriented model with an objective function to minimize the total cost of inventory and human resources. The model associated a utility function (stock value) to each product which accounts for their price, volume, weight, and variance of demands. By minimizing this stock value function, the model maximizes visits to the CUs. The second type (M2) aimed to provide activities schedule that balance the workload over the week days and introduced this objective into M1. The objective function of M2 is to minimize the total manpower use time for all SCM personnel at the time of any given activity. Both models, M1 and M2, are set to perform under several constraints as follows:

(i) Set time restrictions on manpower to accomplish the required activities;
(ii) Direct deliveries are restricted to products received within the current period;
(iii) Demand satisfaction;
(iv) Respect of storage capacity (weight and volume);
(v) No product is received if the supplier does not visit the hospital;
(vi) Products at CU can only be replenished if unit is visited.

Outputs of M1 and M2 produce significant information on SCM personnel's schedules and amount of manpower hours per day distributed among the activities of SCM. Concerning the previous models, the heuristic techniques, TS, and VNS were applied as a solution to M1 and M2. The solutions obtained were compared based on three criteria: (1) carrying cost; (2) uniform workload distribution; and (3) required working time. The best solutions stipulate that spending more time in procurement and inventory control operations than the current situation in hospitals. This suggests that hospitals should order more at specific times and reduce stock levels in central stores. The model also suggested controlling inventory levels in CUs by dedicating a person there to make replenishment decisions.

To better improve logistics, this approach would play critical role by coordinating their procurement and purchasing activities, the information it produces may be used to fix a schedule for the required number of workers to accomplish everyday activities but not the details of this schedule. Instances regarding schedule details include the special skills of these workers, delivery paths, and the assignment of different activities to different workers. The differing pathways have impact on the delivery time while worker activity assignment is controlled by the execution time of each activity, priority relationships between tasks, and break periods. Additionally, while the approach is best suited in performing "what-if" analysis to measure different strategies, it fell short to providing a tight schedule as an optimal solution. Lastly, the approach is computationally expensive. In the experiment setting, the naive assumption was made for small number of products, suppliers, and CUs.

Table 1 gives a snapshot on these simulation models. It is important to note that all models approached the optimization problem at different levels of SCM. In healthcare SCM, optimization reduces the general problem of delivering products to consumers at the cheapest total cost and highest level of service.

Challenges for SM in Healthcare SCM

The pervasive interest in SM for healthcare SCM is bereft with its own challenges. The increased interest in SM for healthcare SCM is not without its challenges. In the light of models discussed above, the most challenges faced by simulation and modeling community in healthcare SCM are as follows.

Collecting Sufficient Amount of Related Input Data: SM projects are devoted data gathering and validation however; a lot of money is wasted in many SM projects because of solving wrong problems as a result of insufficient or irrelevant input data. With regards to the approaches discussed, SM builders collected data from the manually entered historically records of SCM via interviewing SC managers and employees. Even though, this process plays important role to developing a better understanding of the problem, it consumes a lot of time and subject to overwhelming unnecessary details. Also, the manually entered data about the status of inventory in SC is seldom accurate.

SM Validation and Verification: Validation and verification aim to determine the accuracy of the model and the SM project by finding errors and correcting them (Chapurlat et al. 2008).

Implementation: Quite a number of SM studies pertaining to healthcare have shown a conceptual level and only a few report evidence of implementation (Eppich et al. 2011). A study carried out by (Katsaliaki et al. 2011) as cited by Rohleder et al. (2011) surveyed 201 healthcare SM related research studies but found only 11 which reported the implementation of results to healthcare organizations. Our study investigates currently adopted SM eligible for adoption in the healthcare industry thus offers divergent view of the available features and the shortcomings of these models. Additionally, this makes way for recognizing the challenges and issues that need to be addressed to achieve better and more effective models. Mostly, some of the developed models in academic settings are not widely accepted by healthcare organizations. Attributed to these problems are implementation cost and issue of generalization among others.

Implementation Cost. The major challenge for small and medium size organizations is implementation of SM which attracts a significant cost to the healthcare organizations. Embarking on SM projects is capital intensive as it requires expensive Information Communication Technology (ICT) infrastructure while the resources in healthcare settings are scarce and most preferred to be allocated to improve clinical services.

Generalization: Most of the model developments are made specifically to hospitals that they were developed for and cannot be applied to other hospitals. Thus, there is imperative need for generic models with a high degree of flexibility and scalability.

Growth in Models' Size and Complexity: Models for healthcare are rising in terms of size and complexity due to growing number of objects and events in healthcare SCM, and the swift towards partnerships between various hospitals and other SC members. This delays the execution speed in the model in long run. Decision makers need the requisite tool that can provide immediate solutions rather than when the answer is already out of date.

Representation of Human Decision Making: SM in healthcare SCM represents SC entities and relies on modeling resources scheduling and allocation and processes rather than the representation of complex decision making processes made by SC managers (Hassan et al. 2014).

SM Techniques and SCM Problems

Choosing the right kind of technique is critical in aligning SM techniques to mitigate SCM problem while ensuring accurate representation of the problem (Cigolini et al. 2004). In practical terms, modelers are more abreast with SM technique to apply irrespective of the problem (Kalra et al. 2015). Towards helping in this end, authors in (Mardani et al. 2015; Soni et al. 2013) proposed an approach to develop a framework to assist practitioners in selecting the appropriate technique for SCM challenges.

Expert Modelers: The expert modelers are few hence model construction in most cases, is left to inexperienced SC managers and analysts. Yet, constructing good descriptive or optimization models requires huge efforts, experience, and expenses that are, sometimes, more than what an expert modeler can accomplish or more than what a company is willing to invest (Jetter et al. 2014).

Expert Users: SM users must have understanding/knowledge with respect to software and statistics. Nonetheless, most SC managers and analysts are non-experts SM users. Moreover, SM software should be easy to learn with an easy-to-use graphical user interface that helps users in problem definition, design of computer experiments, simulation runs, access ready information, and results analysis. Ultimately, captured results are presented in interpretable and understandable format with the ability to transfer these outcomes in different reporting tools.

Integration of existing models: The integration of existing models is an issue of two levels.

(1) Inter-models integration: as we have seen in Section 3, proposed models perform at different levels of SCM. The advances in integrating these models will have value in saving extra model building efforts; exchanging information between SC members; and reducing overall execution time.

(2) Models legacy system integration: most developed simulation models are independent and standalone tools. Advancements in integrating these with HC legacy systems such as inventory management systems or electronic resources planning (ERP) are critical in order to address the issue of reluctance of sharing information among different SCM members and other decision making entities in hospitals as well as the issue of the lack of and inaccurate input data.

Contemporary Technologies that Support SM in Healthcare SCM

To fully grasp and harness the SM opportunities in healthcare SCM, many and diverse technologies have been tried to meet the challenges outlined above. Some of these technologies may seem unimportant to SCM in healthcare, yet the pervasive popularity and usability advantages offers a paradigm shift that incorporate SCM with some of them leveraging potential problems. Here we briefly discuss some of the most promising technologies.

6.1. Agent-Based Simulation (ABS): ABS is a relatively new paradigm that is based on the concepts of multi-agent systems and robotics from the field of artificial intelligence (AI) (Zbib et al. 2012). ABS embodies a complex system with agents programmed to follow some behavior rules. In this system, agents are capable of making independent decisions which is at variance to objects and entities in conventional simulation techniques. ABS is a bottom-up modeling approach which uses behavior of agents which come as a result of individual system properties emerging from interactions of agents. Recently, agent-based simulation has gained a great deal of publicity because it reveals the complexity of the real world by considering a representation of the system and by producing the unpredictable behavior of a group of people according to their individual decisions (Harrison et al. 2016). Although ABS is more suitable for strategic problems (Gao et al. 2012), in areas of human behavior, information sharing and collaboration its unique features make it more appropriate to simulate problems ranging from the strategic level to the operational level. However, since ABS is computationally intensive it used minimally in industry (Ferrer et al. 2013).

6.2. Radio Frequency Identification (RFID): Radio Frequency Identification (RFID) is seen as one of the contemporary technologies today (Andreev et al. 2015; Kour et al. 2014). RFID is a technology that uses radio signals to communicate with a tag placed in or attached to an object, an animal, or a person which come as tag that store information and can be attached to the items, a wireless network of electronics interrogators that reads the information on the tags; and a middleware that bridges the RFID hardware with enterprise applications. Electromagnetic waves are used for sending and receiving information between tags and readers (Chunli et al. 2012; Sundar et al. 2015). The emergence of RFID technology brought a huge sigh of relief for SCM in healthcare with respect to improving the speed and accuracy of tracking inventories; reducing inventory levels; reducing overhead costs, and improving the efficiency of work process. Accordingly, RFID contributes to mitigate the aforementioned challenges associated with the traditional forms of data collection in SM projects. This was followed by several studies that used SM techniques to solve problems with RFID-enabled SC systems. RFID technology is developing; however, it promises a good opportunity for improving the accuracy and efficiency of SM for healthcare SCM.

6.3. Distributed Simulation (DS): Distributed simulation (DS) depends on the distributed systems technology to enable the execution of a single run of simulation program across multiple interconnected processors (Ray et al. 2012). The application of DS within the context of SCM in general is motivated by the distributed physical environment of SC and the need for information exchange between its also distributed parts and/or members. Distributed Simulation does not only reduce the simulation run time but also integrates the different models that already exist (Caro et al. 2012). Thus, a simulation model of SC can be designed traditionally as a standalone single model run on one computer or using multiple integrated models representing the different parts of the SC that run in parallel on multiple synchronized computers. PDS allows for designing and realizing complex SCM simulation systems that cross hospital boundaries to a wide range of suppliers and consumers. Within PDS-based systems, the different models representing each entity are self-contained with the ability to share the common information as needed.

Various studies have espoused on the prospects of DS for healthcare SC. For instance, Wainer et al. (2011) drew parallel with the run time of the standalone healthcare SC simulation with distributed simulation. They revealed that the run time of the standalone simulation increases exponentially as the size and complexity of the model increases while using DS decreases the execution time for large and complex models. Gaudes et al. (2013) investigated if using DS can speed up the traditional simulations for blood SC in UK. The results showed that DS achieved better performance as the model grows compared to the standalone simulation. One particular challenge for DS lies in properly managing the communication between the distributed computing models or nodes. There are two frameworks suggested to handle this challenge.

(i) Network structure: based on distributed protocols to facilitate the interaction among point-to-point interconnected nodes and to update simulation states.

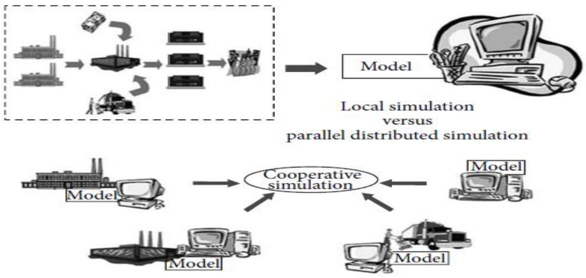

Figure 2: The two paradigms for SCM simulation.

(ii) Centralized structure: based on a centric instrument or software to manage communication between the simulation nodes.

However, the first framework suffers from the problems associated with traditional point-to-point networks which include no support for routing logic and limited support for heterogeneity; and complexity increases as more nodes are added to the simulation. This is supported by the results in Andrade et al. (2007) where the run time of distributed simulations rises exponentially as the number of hospitals increased. The second framework on the other hand, supports flexibility and scalability by separating the communication activities from the model's activities using a message broker. The message broker takes the responsibility to filter, process, and distribute messages as needed between nodes. It uses the node's identity, message type, or message content to perform a logic routing while managing communication between the nodes. It also provides adaptors to generate uniform data formats. Hence, this framework is becoming widely used to develop the parallel distributed simulation (PDS).

6.4. Service-Oriented Architecture (SOA): Service-oriented architecture (SOA) is an architecture that leverages open interconnection standards to represent software or system functions as services through well thought out and stable interfaces specified with a service contract (Sierra 2013). A service only exposes its inter-face on the web while the service's contract specifies the purpose, functionality, constraints, and usage of this service. SOA is driven by the emergence of Web Services which became the preferred method to build SOA environments. SOA allows developers to create their applications using the services provided by different organizations and published on the web. The perceived benefits of SOA include offering on-demand business support, improving dissemination of information, lowering systems complexity, reducing integration cost, and improving efficiency (Hashemi et al. 2013). SOA also increases flexibility in responding to dynamic changes in the application requirements and performance.

In the area of SM development, SOA contributes to mitigate the concerns related to the long development time, integration with legacy systems, implementation costs, and shortage of expert modelers. In simple terms, it provides on-demand simulation services for designers to construct good descriptive SCM models in a short time and lower cost. In addition, adopting SOA in developing simulation models enables designers to adjust models in a flexible and cost-effective manner.

6.5. Cloud Computing (CC). Cloud Computing is a new buzzword that has been in the information technology domain over the years. Cloud Computing (CC) refers to an environment where running application software and its related data are stored on a cluster of servers. This method of storing data on a central computer system provides customers and users access through the Internet (Jadeja et al. 2012). By definition, cloud computing relieve organizations the burden of setting up their own ICT infrastructure from scratch. This burden of ICT infrastructure development and implementation can be shifted to party: the cloud service provider. The cloud service provider responds to the organizations' needs of outsourcing their ICT by offering flexible and scalable service architectures and through "pay as you go" or "on demand" contracts. Cloud Computing brings diversity into the organization's network and server infrastructure. CC can be seen as an evolved model of DS and SOA technologies. The CSP in the cloud provides three major services.

(i) Software as a service (SaaS): provides different services and applications for clients to use over the Internet.
(ii) Platform as a service (PaaS): provides platforms or run-time environments to clients. It offers a wide variety of resources like databases and development environments with basic services to build and deploy clients' applications.

(iii) Infrastructure as a service (IaaS): provides infrastructure resources and allows for remote storage and applications' execution. At this level, the CSP takes care of the daily procedures of using and maintaining systems in the cloud.

The advantages of CC include reduced cost of ICT; flexible payment models such as "pay as you go" or pay per service; highly reliable/available services and resources; up-to-date tools to facilitate applications development; remote and location independent access; reduced ICT management responsibility; ability to handle unexpected higher or lower demands for resources (scale up or scale down); ability to share resources and costs across a large pool of clients and offers security mechanisms. CC solutions can support the simulation community through the following:

(i) Providing the computing platform and infrastructure for model builders to develop their models and/or to execute simulations and get results without the cost of ownership;

(ii) Providing the simulation software in a SaaS manner in which every software function is treated as service.

In addition, CC saves time and efforts consumed by the software process, Simulation Software-as-a-Service, SimSaaS, provides the advantages of scalability and the multi-tenancy architecture (MTA). MTA maximizes sharing of software, data and data schemas by multiple tenants/partners. Using MTA, SimSaaS provides the simulation system with the ability to add/remove/modify partners; address the partners' accessibility controls; distinguish partners' simulation interaction message during executions; and isolate partners' own specific data. In comparison to the DS technology discussed earlier, SimSaaS presents promising potentials to meet most of the challenges for SM of healthcare SCM. Several recent studies explored in detail how SM can benefit from CC. Other studies propose solutions for SM in the cloud. For an example, Bahrami et al. (2015) and Tsai et al. (2011) proposed SimSaaS with an MTA configuration model and a cloud-based runtime to support fast and scalable simulation development to be run in a flexible cloud environment. Ficco et al. (2017) present SimSaaS architecture to support automatic deployment of simulation services to run experiments defined by clients.

Among aforementioned technologies, RFID and DS are still the only two practically tried technologies to aid SM for SCM in general and in the healthcare context in particular. The rest are still at the conceptual level. This implies that more robust research and development activities are required in these areas to realize the opportunities of these technologies in enhancing SM capabilities of supporting decisions making in healthcare SCM.

Concluding Remarks

Years have gone by where many organizations including healthcare started using computer modeling and simulation to boost and sustain their day-to-day operations. The emergence of simulation modeling (SM) tools has helped develop specific functional and decision systems that provided flexibility, specificity, and consistency. Healthcare simulation modeling is a way to test changes in a computerized environment that will hopefully put forward ideas for improvements and subsequent implementation. The idea put forward in the research literature on various models was idealized to support the healthcare SC decision making process. The know-how gained and the possible potential value of how models may be applied is a useful tool in promoting better understanding to these processes.

SM allows healthcare SC organizations to proffer divergent scenarios for decision making while ensuring openness in communication to further appreciate the inner workings of a potential sophisticated system. This is surmised on direct feedback on suggested modifications.

Further, SM in healthcare SCM demands the organization in question to be well structured, integrated, and prepared to implement and use such a system. There are diverse strategies (alternatives) for modeling healthcare SCM that can be used depending on the problem and the results the organization is trying to achieve. As steps are being developed for the success of simulation, it should be viewed not just in the use of current and future technologies but also its application to the clinical environment. As new technologies emerge to mitigate concerns regarding implementation, potential impact, and value added for healthcare SC processes, it then becomes very imperative for healthcare organizations to realize the likelihood of simulation modelling to enhance their operations and maximize the benefits.

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