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Abstract

Purpose – Customer support has always been considered a competitive advantage in many industries. In recent years, firms have begun to provide customers with a high-quality service experience, in order to attract more customers and achieve higher customer satisfaction. Although customer service and satisfaction have been discussed by other researchers, to the knowledge, there has been no dynamic and intelligent way to model and optimize customer support systems for product and service providers. The purpose of this paper is to develop a modeling method for customer support optimization.

Design/methodology/approach – In this study, a system dynamics (SD) model has been formulated to investigate the dynamic characteristics of customer support in an IT service provider. The proposed simulation model considers the dynamic, non-linear, and asymmetric interactions among its components, and allows study of the behavior of the customer support system under controlled conditions. Furthermore, a particle swarm optimization method was developed to investigate the proper combination of parameters and strategy development of the support center.

Findings – This paper proposes a novel modeling, simulation, and optimization approach for complex customer support systems of information and communications technology (ICT) service providers. This method helps managers improve their customer support systems. Moreover, the simulation results of the case study show that ICT service providers can gain benefit by managing their customer service dynamically over time using the proposed artificial intelligent multi-parameter modeling and optimization method.

Research limitations/implications – The proposed holistic modeling approach and multi-parameter optimization method will greatly help managers and researchers understand the factors influencing customer support. Moreover, it facilitates the process of making new improvement strategies based on provided insights.

Originality/value – The paper shows how SD simulation and multi-parameter optimization can provide insights into the field of customer support. However, the existing literature lacks a holistic view of these kinds of simulation systems, as well as a multi-parameter optimization method for SD methodology.

Keywords Service quality, System dynamics, Customer support modelling and simulation, Multi-parameter optimization, Swarm intelligence

Paper type Research paper

1. Introduction

In recent years, service quality largely affects customer satisfaction with a product or service (Bienstock *et al.*, 2015; Bansal and Taylor, 2015). Customer service is an element of service quality that is frequently discussed, but often overlooked in practice. However, in the past few years, organizations have begun to realize that customer service is a major source of revenue (Ruben *et al.*, 2015; Crotts and Ford, 2008). The better experience with customer support causes greater customer loyalty of customers (Teng and Barrows, 2009). Akbar *et al.* (2010) claimed that delivering superior customer service is essential to an organization's viability, based on the fact

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that it increases competitive advantage by developing customer loyalty and serves as an excellent word of mouth advertisement tool. This loyalty strongly affects market share and profitability (Crotts and Ford, 2008). Information and communications technology (ICT) service providers in particular need to ensure that appropriate customer support is available for their products, including installation, operation, maintenance, user training, and telephone support (Yee *et al.*, 2010). In order to improve the system of customer service, the first step is to conceptualize and model its dynamics over a defined period of time.

Dynamic modeling of systems has gone beyond its previous focus on oscillations, to questions that more straightforwardly call for exchanges, such as effectiveness, productivity, and development. In many situations, decision makers and system modelers strive to optimize a system by changing its parameter values in subject to minimize or maximize one or more variables in the model. Nowadays, the availability of computer software packages allows a wide range of system professionals and beginners to design and implement dynamic models of systems. After formulating a full mathematical system dynamics (SD) model known as a stock-flow diagram, the model can be simulated with different combination of parameter values. Each combination may cause different behavior of the system under investigation over the period of simulation time. Decision makers usually prefer the optimal values for some variables of model. These values are dependent on the model structure, parameter values, simulation period, etc. The simplest approach to optimize the parameters is to divide the range of each parameter value into discrete points, and to test each combination, one by one. This approach can only be applied to small SD models since it becomes rebellious when introduced into larger systems. Another characteristic of non-linear complex dynamic models is that the space of parameters often exhibits multiple equilibria. This paper develops a stochastic optimization technique based on a particle swarm optimization (PSO) algorithm as a means of overcoming this dimensionality and the multiple equilibria characteristic. Moreover, the proposed approach does not rely on specific information about the system under investigation.

The rest of the paper is set out as follows. The next section considers the existing literature on customer service modeling and optimization, SD models and tools. Following that is an introduction to swarm intelligence and PSO algorithms. Next, the proposed method is described with a case study of calls support service for clients. The final section includes practical implications and conclusions.

2. Literature review

2.1 The concept of customer service modeling and optimization

Customers appraise products based on the purchase and consumption experiences over time (Fournier and Mick, 1999). A high level of customer service provided to customers is seen by them as a measure of quality, for them and acts as a source of the firm's competitive advantage (Goffin, 1998). Customer service is to ensure that the quality of goods and services meet the expectations of those who use them. It is a primary element by which customers estimate the value of a company (Moses, 1999). Customer satisfaction manifests in repeat purchase behavior (Sharma and Lambert, 1990).

From a conceptual perspective, there are studies reported in the literature on the theoretical frameworks and models that support the relationship between main concepts such as customer support, assessment, quality of service, selection, and implementation of an appropriate customer support strategy. For example, Piccoli *et al.* (2009) proposed a new conceptual framework to explain the selection and performance of the appropriate service strategy that meets customers' process completeness expectations in electronic commerce. Hsieh and Yuan (2010) developed a conceptual framework and a model of customer expectation management, as well as a reference model of service experience design which are regarded as the basic foundation to model the processes of service experience design for service operation strategies simulating and testing. Elmorshidy (2011) develop a new theoretical framework for customer e-service quality success.

On the other hand, some researchers have developed formulized models or statistical surveys, in order to simulate the actual behavior of a customer support service center. In their approach, previous frameworks, conceptual models, and literature are used to plan and develop a model of a real-world system. For example, Shankar *et al.* (2006) investigated the relationship between field staffing levels and customer waiting times in IT hardware support by using statistical analysis and survey in the system. Pérez and Bosque (2015) determined that customer support influences the way customers form their perceptions of corporate social responsibility practices in the banking industry. Baraka *et al.* (2015) identified the dimensions for call centers that are facing challenges in customer support. Elmorshidy *et al.* (2015) suggest that factors such as usefulness, ease of use and attitude have a significant influence on customers' intention to use live customer support chat services.

There are two significant research trends in the literature, one of which is derived from Shankar *et al.* (2006), while the other came from the work of Hsieh and Yuan (2010). Shankar *et al.* (2006) supported an optimization perspective that only supports one parameter of a complex and multi-dimensional system. This implies that, there are very few studies in the literature that support simulation, optimization and also consider the system as a complex and multi-dimensional entity that needs a more detailed modeling. Previously mentioned studies can be compared in terms of their research method, modeling methodology/framework, simulation and optimization approach, industry applications, and basic findings, as shown in Table I.

These studies can be classified into two main categories, depending on whether they accept a simulation-optimization approach or they develop conceptual frameworks, as depicted in Figure 1. As shown in Figure 1, two main perspectives on customer support are obtained from previous studies: edge and blend view. "Edge view" is a category of pure methods or studies that considers conceptual or simulation-optimization approaches. On the other hand, "blend" view is about conceptualization and simulation of a practical support system.

2.2 SD and policy option analysis

SD, originated by Forrester (1958), is a system analysis approach that is concerned with creating models or representations of real-world problem situations and studying their dynamics over time. This modeling and simulation approach focusses upon an understanding of feedback and feedforward relationships, and the model construction requires the analyst to create the relationships between the various stage variables and rate variables. In this method, the research problem is defined using qualitative and quantitative information, and consequently reflected in a causal diagram. This causal diagram expresses the equations that make connections among variables and concepts in the suggested model. The researcher must assign values to several parameters, to assure that the model simulation reproduces historical data under plausible conditions. If the proposed model is coherent with the past and present situation, the researcher can simulate the impact of different policies and changes on the system.

Table I. Customer support assessment, simulation, and optimization literature

Researcher	Research method	Modeling methodology/ framework	Simulation	Optimization	Industry	Basic findings
Goffin (1999)	Empirical/ case study	Cross-case analysis	No	No	Cross-industry of distribution channels	Insights on how different channels and strategies affect the quality and efficiency of customer support
Crossno *et al.* (2001)	Survey	ACSAHL/ SERVQUAL	No	No	Academic	More respondents preferred the shorter proposed instrument to the longer and more complex SERVQUAL instrument
Hung *et al.* (2003)	Conceptual	Lambert and Sharma's performance evaluation matrix	No	No	Cross-industry	Standardized Service quality performance matrix for standardizing the procedures of service quality assessment
Shankar *et al.* (2006)	Empirical/ field survey	Statistical analysis	Yes	Yes (single-parameter)	IT (hardware)	Increasing field staffing levels obscures the significant difference between the customer waiting times
Piccoli *et al.* (2009)	Conceptual	Process completeness	No	No	Electronic commerce	Selection and implementation of the appropriate service strategy that meets customer's process completeness expectations
Hsieh and Yuan (2010)	Conceptual	System dynamics	Yes	No	Cross-industry	A reference system dynamics model of service experience design
Elmorshidy (2011)	Theoretical	Integrated gaps model of service quality	No	No	Cross-industry	A new theoretical framework for customer e-service quality success
Elmorshidy *et al.* (2015)	Conceptual/ survey	Hierarchical regression	No	No	Cross-industry	Factors such as usefulness, ease of use and attitude have a significant influence on customers' intention to use live customer support chat services
Baraka *et al.* (2015)	Empirical (case study)	Design reality gap	Yes	No	Cross-industry	Identifying the dimensions for the call centers that are facing challenges in customer support
Pérez and Bosque (2015)	Empirical (case study)	Cluster analysis	No	No	Banking	The results confirm the relevance of motivational attribution when socially oriented and highly involved customers evaluate corporate social responsibility
This Paper	Conceptual/ emperical	System dynamics/ PSO	Yes	Yes (multi-parameter)	Information technology/call support centers	An integrated system dynamics model with PSO in order to model and multi-parameter optimization of customer service experience in IT call support centers

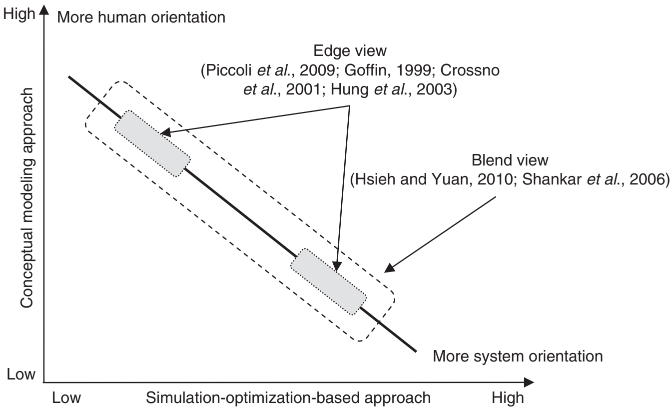

Figure 1.
Perspectives on customer support studies

An important aspect of SD, as with any other simulation approach, is the use of an optimization approach in order to investigate the policy space and parameters. This allows the researcher to find the best combination of parameter values, based on a specified objective function or variable. Optimization fits naturally into SD, thus the two are complementary approaches (Duggan, 2005). The first research on SD optimization was presented by Coyle (1985), Kivijarvi and Tuominen (1986), and Macedo (1989). But since then, optimization has become a poor relation in the SD world. SD modelers have applied model optimization in different contexts (Graham and Ariza, 2003): optimization of policies and decisions; model calibration (Lyneis *et al.*, 1996); and simulating very complex decision processes, e.g. Homer (1999). In the first category, key decision levers are represented as parameters in the model. These parameters are changed automatically via an optimization algorithm, such as the case which is described in this paper. This could be termed as the parameter perspective for optimization approaches. For this group of optimization, it is assumed that the decision maker is pleased with the equations, and the only uncertainty remains as to what values the parameters should have. The second category is where the objective function is a measure of goodness of fit within available data. The third group is where a micro-level operations research model is necessary to generate the parameters driving a macro behavior.

Nowadays, SD has a lot of applications in many fields such as supply chain management (Langroodi and Amiri, 2016), environmental science (Bastan *et al.*, 2013), nuclear power development (Guo and Guo, 2016), energy policy development (Hosseini and Shakouri, 2016), human health improvement (Abidin *et al.*, 2014), production and inventory system (Poles, 2013), material science (Cheng and Tang, 2013), and information and service science (Sun and Luo, 2012). In this study, the authors accept the SD optimization of policies and decisions and use it to achieve a realistic, reflective, and optimized system form for a greater understanding of the target system.

2.3 PSO

PSO (Kennedy *et al.*, 2001) is an evolutionary computational population-based search algorithm which is inspired by the simulation of the social behavior of particles, such as bird flocking or fish schooling and swarming in searching for their food. Although the PSO algorithm was primarily developed as a tool for modeling social behavior, it has been applied in many different areas, such as structural design (Perez and Behdinan, 2007), pattern recognition (Chao and Tsai, 2010), robotics (Wang and Liu, 2010), as well as energy conversion and management (Shayeghi *et al.*, 2010). Its key concept is that potential solutions are flown through hyperspace and are accelerated toward better or more optimum solutions. In this approach, the concept of fitness is used and termed particles or sometimes individuals are candidate solutions to a specific problem. Each of these particles modifies its flying, based on the flying experiences of both itself and its partners. It keeps records of its coordinates in hyperspace which are associated with its previous best fitness solution, and also of its colleague, in proportion to the overall best value obtained up to the present time by any other particle in the population. The responses between the individual and group values act as a variety of response. The population is replying to the quality factors of the prior best individual values and the prior best group values.

3. The proposed method

In order to deal with the complexity, non-linear relationships, and existence of feedback loops in customer support services, it is necessary to employ SD modeling method first. The conceptual model of the proposed approach is depicted in Figure 2.

The steps of the proposed approach are as follows.

3.1 Step 1: defining modeling goals

In the first step, optimization targets should be identified and clearly declared. These targets usually come from some problems in the support systems. For example, one common problem in customer support services is the long average waiting time that customers experience. This significantly affects the customers' perception of quality and consequently influences their loyalty. In this case, the target would be to investigate how a customer service management system could lower the average waiting time for clients or customers.

3.2 Step 2: dynamic modeling

According to Maani and Cavana (2000), SD has systematic iterative procedural steps, which are problem structuring, causal loop modeling, dynamic stock-flow modeling, scenario planning and modeling, and implementation. From this point of view, in order to model a system, analyzers should start by defining the problem or the issue at hand and identifying the scope and the boundaries of the study. Next, the causal relationships and feedback loops in the system should be visualized as a causal loop diagram. Following that, this conceptual model of the system should be formulized in terms of stock and flow, based on the Principle of Accumulation. After formulizing stock-flow diagrams, it would be possible to study different scenarios and policies in the model. In the final step, optimized policies would be identified qand implemented.

In the proposed method, policy evaluation and optimization are enhanced by a novel PSO-based algorithm. Due to the complexity of this optimization process (e.g. there are a large number of different variables in the system), the system's initial variables and their feasible variation ranges are estimated by domain experts who have knowledge about the system under investigation. In this manner, the method also uses a sense of human-oriented optimization in order to obtain better and more feasible results.

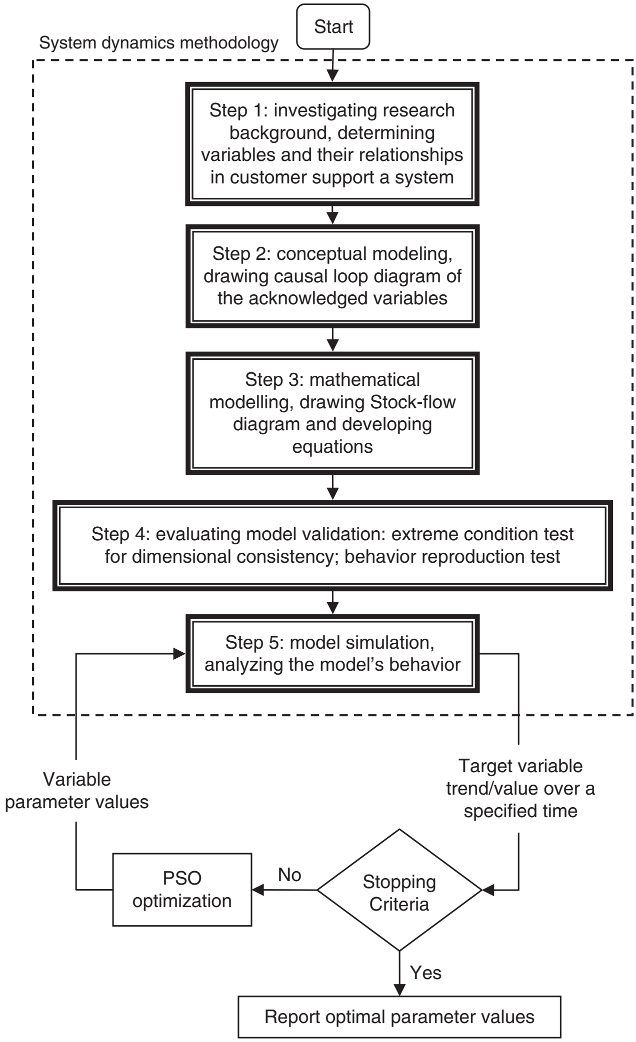

Figure 2.
The conceptual model of the proposed approach

3.3 Step 3: applying PSO and optimization

After formulating the stock-flow diagram and the equations of the dynamic model, decision variables and the target are identified in the model. In this step, PSO is integrated into the dynamic model and searches the available and feasible space to find the best combination of variable values based on the target variable. Each time PSO selects a group of variables, it connects with the SD model and waits for the target variable trend or its value over a specified time. As depicted in Figure 2, after receiving the decision variable's parameter values, SD runs for a specific period of time and reports the variable changes back to the PSO algorithm. This cycle runs until an optimized value for the target is reached. This implies the end point for the PSO algorithm, which can be defined as no significant change in target value over a defined number of cycles.

4. Empirical study

The (anonymized) company whose case we examine here is the first Iranian general contractor for the oil and gas industry, specializing in offshore engineering, procurement, construction, pipe coating, pipe laying, and installation of jackets, TopSites, etc. The company designs, procures, builds, installs and services a complete range of offshore surface and partial subsurface infrastructure for the offshore oil and gas industry.

In addition to improving the quality of service, one of the main purposes of building this dynamic model is increasing customer satisfaction in this client service system. The support department receives incoming support requests every day. Some requests would be answered (with an answering rate) and some of them remain unresolved. These unresolved issues usually occur either because support employees are not available, or because the complexity of issues exceeds the staffs' domain knowledge. "total support requests" refers to the sum of "answered requests" and "no answers." This support department also keeps track of "current satisfied clients" which reflects the difference between the "client satisfaction rate" and the "client dissatisfaction rate." Figure 3 shows the first part of stock-flow diagram of this dynamic system.

"Satisfaction rate" is determined by "current satisfied clients" and "average waiting time." satisfaction increases as average waiting time for each client decreases. "average time satisfaction" is calculated as "satisfaction rate" divided by "current satisfied clients." finally, "average client satisfaction" is determined by "average knowledge level" of employees and the "average time satisfaction" variable. The second part of this stock-flow diagram is depicted in Figure 4.

The rest of the model describes the structure of "employee's knowledge," "hiring and firing," "productivity," "motivation," etc. following the mathematical formulation of the model, its dimensional consistency and behavior at extreme conditions are assessed and verified. In this verification test, the consistency and significance of each variable's behavior was tested by setting the parameters of their extreme values. Furthermore, a behavior reproduction test was utilized (qualitatively and quantitatively) where normality of the residuals is examined and confirmed. Moreover, the adequacy level of the model boundaries was confirmed by asking for the ideas of five experts (boundary

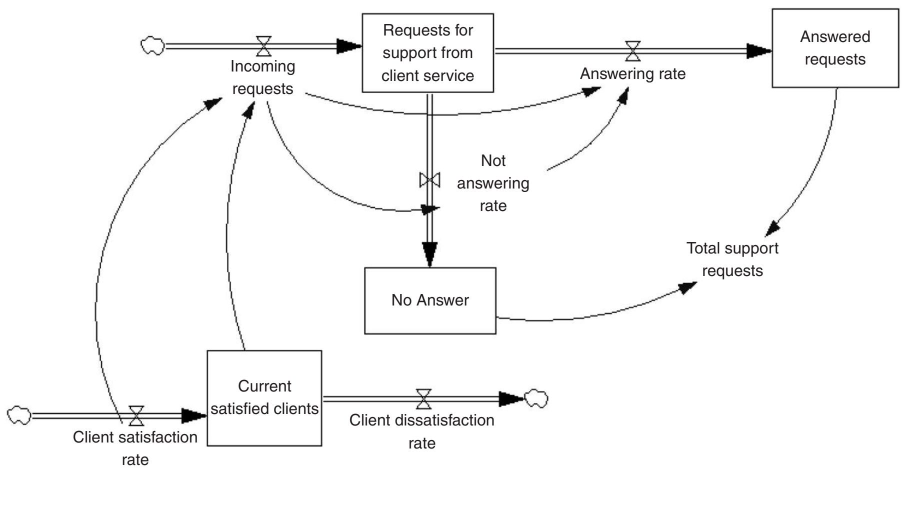

Figure 3. The stock-flow diagram of support requests (Part 1)

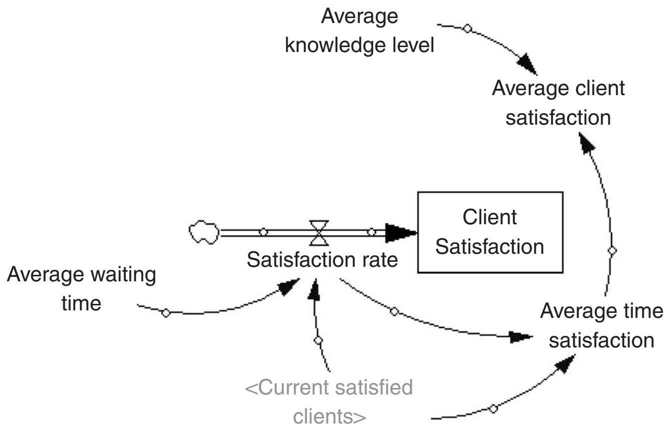

Figure 4.
The stock-flow diagram of support requests (Part 2)

adequacy for the structure test), and the dimensions of all variables in all equations were reviewed and it was determined that the dimensions of both sides of the equations were in balance (dimensions consistency test).

The model is simulated for 24 months (Step = one month) as simulation control parameters. Currently, the most common optimization method for SD models is expert tuning. In this approach, a group of domain experts selects different combinations of parameters according to their knowledge, and observe the output results. We have also conducted a similar human-oriented optimization approach, and the resulting "average waiting time" variable is depicted in Figure 5.

As described previously, one of the most important variables in each support system is "average waiting time" for different clients or customers. Thus, the purpose of this optimization was to select a set of parameter values which produced a lower degree of average waiting time by support system. Thus, the objective function used in this optimization was the average waiting time for 24 months. The optimization method relied on a PSO (Kennedy *et al.*, 2001), but the optimization variables originated from experts who have considerable knowledge about this support system case. These variables, and their feasible ranges of variation, are indicated in Table II.

Furthermore, PSO parameters are shown in Table III.

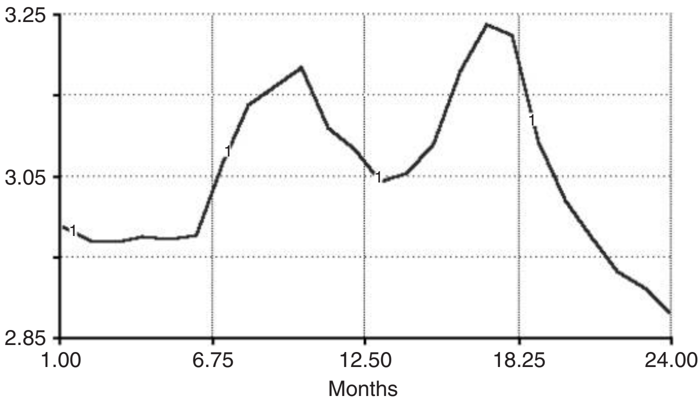

Figure 5.
The behavior of "average waiting time" variable over 24 months

Variable name	Initial value (originated from experts or data logs)	Feasible variation range
Client dissatisfaction	10	[8, 12]
Learning productivity	0.4	[0.3, 0.5]
Client satisfaction	50	[40, 60]
Lost knowledge from erosion	80	[60, 90]
Skills from new hire	40	[30, 50]
Customer support initial employee	100	[80, 120]
Knowledge	8,000	[7,500, 8,500]
Initial support requests	120	[110, 130]
Initial current satisfied clients	1,000	[950, 1,050]

Table II. The optimization variables

Parameter name	Value
Max particle velocity (this allows each component to have its own max velocity)	4
Maximum number of iterations (epochs) to train	100
Population size (number of particles)	24
Acceleration constant 1 (local best influence)	2
Acceleration constant 2 (global best influence)	2
Initial inertia weight	0.9
Final inertia weight	0.4
Epoch when inertial weight at final value	1,500
Minimum global error gradient	1e-25
Epochs before error gradient criterion terminates run	150
PSO seed	All random
Dimensions	9

Table III. The PSO algorithm parameters

The PSO algorithm was run with the specified parameter values in Table II. In order to transmit SD data and use PSO for SD simulation and analysis, the whole SD model and data were translated into equations via the Matlab software package. Matlab software makes it possible to simulate the SD model and to perform the PSO function at the same time. In this optimization approach, each epoch of PSO is a full simulation of a SD model for 24 months. In each SD model simulation, the "average waiting time" variable is captured and is reported as the objective function value. The results of this optimization are depicted via the value of "average waiting time" variable vs the epoch number in Figure 6.

The optimal parameter values are also reported in Table IV.

The minimum and global best value for the "average waiting time" variable is 0.305 minutes. This value is about 950 percent better than previous simulation. The comparison between the previous human-oriented and particle swarm-oriented optimizations are depicted in Table V.

The optimization resulted not only in the final value, but also it changed the behavior of the "average waiting time" variable over the specified time period. As depicted in Figure 7, "average waiting time" decreased over 14.5 months, after which it increased for about two months and finally decreased for the rest of simulation period.

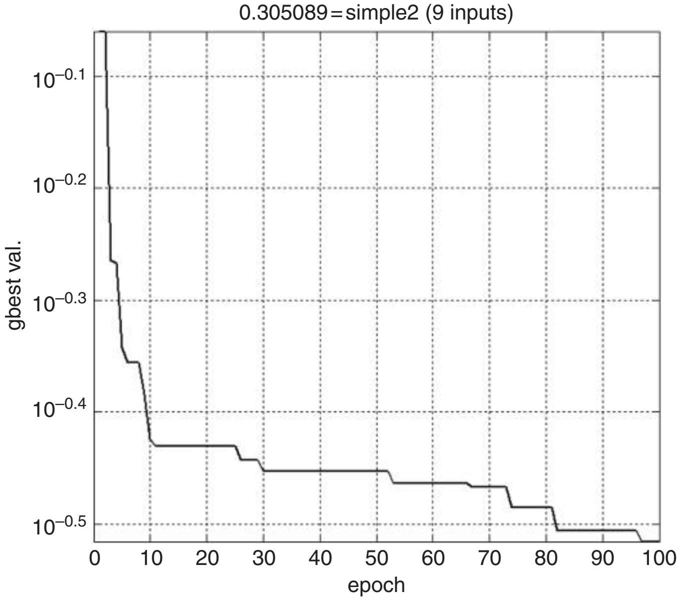

Figure 6.
Changes in the global best of PSO (average waiting time parameter value)

Table IV.
The optimal parameter values for minimization of "average waiting time" variable

Variable name	Optimal value
Client dissatisfaction	12
Learning productivity	0.5
Client satisfaction	45.6
Lost knowledge from erosion	60
Skills from new hire	50
Customer support initial employee	102
Knowledge	8,310
Initial support requests	116
Initial current satisfied clients	993

Table V.
The comparison of optimization methods

Optimization type	Trend/behavior	Average waiting time (minutes)	Time (minutes)
Human/expert oriented	Up-down/oscillation	2.9	76
Particle swarm oriented	Continues decreasing	0.305	3

5. Conclusions

This paper has demonstrated a novel integrated PSO and SD optimization method that can discover the optimal combination of parameters for a given complex environment. The results are briefly discussed and the behavior of the model was analyzed under a specific scenario. This new optimization algorithm starts with developing a detailed SD model of a system and uses a PSO algorithm in order to optimize the parameter values subject to an objective function. In this case, the objective function was to minimize the value of the "average waiting time" variable in an IT support department. The findings demonstrated that this approach has an outstanding influence over the value of the target variable in a short CPU runtime. On the other hand, this optimization approach helps strategic decision makers to learn more about the problem situation and speeds refinement of the underlying feedback structure of SD models.

In real-world problem situations, not all variables in simulation can be accessed and changed directly by system's owner or supervisor inside the system. On the other hand, some variables can be altered internally in the system under investigation. This is based on this fact that some variables are exogenous and some are endogenous in SD models. For example, "skills from new hire" can be increased by new hiring programs, improved tests, and training courses before employing new staff. Also, "customer support initial employee" can be increased easily by new hiring of employees. But decreasing some variables like "initial support requests" cannot be done directly and should be planned in the system with appropriate guidelines. The most important value of this model (changing parameter values based on a scientific platform) is the insights which is generated from this method. This optimization method seeks the specific, often extreme, conditions that are most important for strategic decision making. This can immensely speed refinement of the underlying feedback structure. Another important issue in using this approach is that of careful selection of parameters and their permitted ranges for optimization. All variables in these ranges must be feasible and applicable from a managerial outlook. Previous studies such as Shankar *et al.* (2006), Hsieh and Yuan (2010), and Baraka *et al.* (2015) do not provide decision makers with simulation and optimization approaches with multi-parameter attribute. However, these empirical and other theoretical studies (Elmorshidy *et al.*, 2015; Pérez and Bosque, 2015; Hung *et al.*, 2003) can suggest better concepts and variables in order to better modeling of the customer support systems.

There are some limitations that may be considered for this study. The first limitation is that the practical application was performed in a specific company. This firm is large and profitable; on the other hand, small and medium firms might encounter different strategies and interpretation about simulation and optimization results. The second limitation of this study is that a time horizon of 24 month is considered. Other periods might change the behavior of parameters and consequently the optimization results. The third limitation is that a specific dynamic model is created for modeling support service; other dynamic models can also be utilized. In this way, the approach is the same but this might cause different results of optimization.

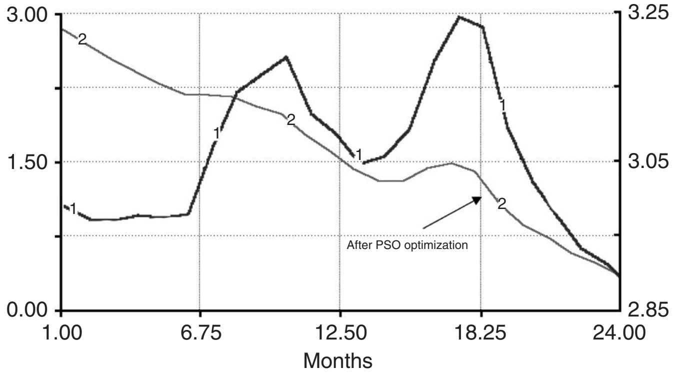

Figure 7.
The behavior of "average waiting time" after the optimization of parameter values

There are also various possible avenues for future research on the topic of modeling and optimization in customer support field. First and most significantly, in this study, the optimizations is performed only by using parameters of a dynamic model. However, optimization algorithms can used in order to change the structure of the model (equations) and parameters at the same time. Second, using newer and more efficient optimization algorithms could be considered in future research. Third, the presented multi-parameter optimization was illustrated in the ICT sector customer support. However, other sectors are possible as research avenues. Fourth, other systems approaches can be used as the modeling tool rather than SD such as fuzzy cognitive maps.

References

Abidin, N.Z., Mamat, M., Dangerfield, B., Zulkepli, J.H., Baten, M.A. and Wibowo, A. (2014), "Combating obesity through healthy eating behavior: a call for system dynamics optimization", *PloS ONE*, Vol. 9 No. 12, pp. 114-135.

Akbar, S., Som, A., Wadood, F. and Alzaidiyeen, N. (2010), "Revitalization of service quality to gain customer satisfaction and loyalty", *International Journal of Business & Management*, Vol. 5 No. 6, pp. 113-122.

Bansal, H.S. and Taylor, S. (2015), "Investigating the relationship between service quality, satisfaction and switching intentions", *Proceedings of the 1997 Academy of Marketing Science (AMS) Annual Conference*, pp. 304-313.

Baraka, H.A., Baraka, H.A. and EL-Gamily, I.H. (2015), "Information systems performance evaluation, introducing a two-level technique: case study call centers", *Egyptian Informatics Journal*, Vol. 16 No. 1, pp. 9-22.

Bastan, M., Abdollahi, F. and Shokoufi, K. (2013), "Analysis of Iran's dust emission with system dynamics methodology", *Technical Journal of Engineering and Applied Sciences*, Vol. 3 No. 24, pp. 3515-3524.

Bienstock, C.C., Mentzer, J.T. and Kahn, K.B. (2015), "How are service firms measuring and managing service quality/customer satisfaction?", *Proceedings of the 1996 Academy of Marketing Science (AMS) Annual Conference*, pp. 161-171.

Chao, S.M. and Tsai, D.M. (2010), "Anisotropic diffusion with generalized diffusion coefficient function for defect detection in low-contrast surface images", *Pattern Recognition*, Vol. 43 No. 5, pp. 1917-1931.

Cheng, G.P. and Tang, D. (2013), "System dynamics mechanism analyses on building materials enterprise factoring risk", *Advanced Materials Research*, Vol. 683, pp. 762-766.

Coyle, G.R. (1985), "The use of optimization methods for policy design in a system dynamics model", *System Dynamics Review*, Vol. 1 No. 1, pp. 81-91.

Crossno, J.E., Berkins, B., Gotcher, N., Hill, J.L., McConoughey, M. and Walters, M. (2001), "Assessment of customer service in academic health care libraries (ACSAHL): an instrument for measuring customer service", *Bulletin of the Medical Library Association*, Vol. 89 No. 2, pp. 170-176.

Crotts, J.C. and Ford, R.C. (2008), "Achieving service excellence by design: the organizational alignment audit", *Business Communication Quarterly*, Vol. 71 No. 2, pp. 233-240.

Duggan, J. (2005), "Using multiple objective optimisation to generate policy insights for system dynamics models", *Proceedings of the 23rd International Conference of the System Dynamics Society, Boston, MA, July 17-21*.

Elmorshidy, A. (2011), "Benefits analysis of live customer support chat in E-commerce websites: dimensions of a new success model for live customer support chat", *2011 10th International Conference on, Machine Learning and Applications and Workshops (ICMLA), Vol. 2, IEEE*, pp. 325-329.

Elmorshidy, A.M., Mostafa, M., El-Moughrabi, I. and Al-Mezen, H. (2015), "Factors influencing live customer support chat services: an empirical investigation in Kuwait", *Journal of Theoretical and Applied Electronic Commerce Research*, Vol. 10 No. 3, pp. 63-76.

Forrester, J.W. (1958), "Industrial dynamics: a major breakthrough for design markers", *Harvard Business Review*, Vol. 26 No. 4, pp. 37-66.

Fournier, S. and Mick, D.G. (1999), "Rediscovering satisfaction", *Journal of Marketing*, Vol. 63 No. 4, pp. 5-23.

Goffin, K. (1998), "Customer support and new product development: an exploratory study", *Journal of Product Innovation Management*, Vol. 15 No. 1, pp. 42-56.

Goffin, K. (1999), "Customer support: a cross-industry study of distribution channels and strategies", *International Journal of Physical Distribution & Logistics Management*, Vol. 29 No. 6, pp. 374-398.

Graham, A.K. and Ariza, C.A (2003), "Dynamic, hard and strategic questions: using optimization to answer a marketing resource allocation question", *System Dynamics Review*, Vol. 19 No. 1, pp. 27-46.

Guo, X. and Guo, X. (2016), "Nuclear power development in China after the restart of new nuclear construction and approval: a system dynamics analysis", *Renewable and Sustainable Energy Reviews*, Vol. 57, pp. 999-1007.

Homer, J.B. (1999), "Macro- and micro-modeling of field service dynamics", *System Dynamics Review*, Vol. 15 No. 2, pp. 139-162.

Hosseini, S.H. and Shakouri, H. (2016), "A study on the future of unconventional oil development under different oil price scenarios: a system dynamics approach", *Energy Policy*, Vol. 91, pp. 64-74.

Hsieh, Y. and Yuan, S.T. (2010), "Modeling service experience design processes with customer expectation management: a system dynamics perspective", *Kybernetes*, Vol. 39 No. 7, pp. 1128-1144.

Hung, Y.H., Huang, M.L. and Chen, K.S. (2003), "Service quality evaluation by service quality performance matrix", *Total Quality Management & Business Excellence*, Vol. 14 No. 1, pp. 79-89.

Kennedy, J., Eberhart, R.C. and Shi, Y. (2001), *Swarm Intelligence*, Morgan Kaufmann Publishers, New York, NY, pp. 141-174.

Kivijarvi, H. and Tuominen, M. (1986), "Solving economic optimal control problems with system dynamics", *System Dynamics Review*, Vol. 2 No. 2, pp. 138-149.

Langroodi, R.R.P. and Amiri, M. (2016), "A system dynamics modeling approach for a multi-level, multi-product, multi-region supply chain under demand uncertainty", *Expert Systems with Applications*, Vol. 51 No. 1, pp. 231-244.

Lyneis, J.M., Reichelt, H.S. and Bespolka, C.G. (1996), "Calibration statistics for life-cycle models", in Richardson, G.P. and Sterman, J.P. (Eds), *Proceedings of the 1996 System Dynamics Conference*, Vol. 2, System Dynamics Society, Cambridge, MA, pp. 425-428.

Maani, K.E. and Cavana, R.Y. (2000), *Systems Thinking and Modelling: Understanding Change and Complexity*, Prentice Hall, Auckland.

Macedo, J.A. (1989), "Reference approach for policy optimization", *System Dynamics Review*, Vol. 5 No. 2, pp. 148-175.

Moses, B.H. (1999), "Achieving excellent customer service through education, competency assessment, and accountability", *MLO: Medical Laboratory Observer*, Vol. 31 No. 2, pp. 41-56.

Pérez, A. and Bosque, I.R. (2015), "How customer support for corporate social responsibility influences the image of companies: evidence from the banking industry", *Corporate Social Responsibility and Environmental Management*, Vol. 22 No. 3, pp. 155-168.

Perez, R.E. and Behdinan, K. (2007), "Particle swarm approach for structural design optimization", *Computers & Structures*, Vol. 85 No. 19, pp. 1579-1588.

Piccoli, G., Brohman, M.K., Watson, R.T. and Parasuraman, A. (2009), "Process completeness: strategies for aligning service systems with customers' service needs", *Business Horizons*, Vol. 52 No. 4, pp. 367-376.

Poles, R. (2013), "System dynamics modelling of a production and inventory system for remanufacturing to evaluate system improvement strategies", *International Journal of Production Economics*, Vol. 144 No. 1, pp. 189-199.

Ruben, C.C., Paparoidamis, N.G. and Chung, C. (2015), "The impact of service quality, relationship satisfaction, trust and commitment on loyalty: an empirical investigation in a business-to-business services context", *Revolution in Marketing: Market Driving Changes*, Springer International Publishing, pp. 91-185.

Shankar, R., Vijayaraghavan, P. and Narendran, T. (2006), "Modeling customer support performance in Indian IT hardware industry", *Journal of Modelling in Management*, Vol. 1 No. 3, pp. 232-254.

Sharma, A. and Lambert, D.M. (1990), "Segmentation of markets based on customer service", *International Journal of Physical Distribution & Logistics Management*, Vol. 20 No. 4, pp. 19-27.

Shayeghi, H., Shayanfar, H.A., Safari, A. and Aghmasheh, R. (2010), "A robust PSSs design using PSO in a multi-machine environment", *Energy Conversion and Management*, Vol. 51 No. 4, pp. 696-702.

Sun, X. and Luo, N. (2012), "System dynamics model and simulation of incentive synergy in knowledge alliance", *Advances in Information Sciences & Service Sciences*, Vol. 4 No. 21, pp. 264-276.

Teng, C. and Barrows, C.W. (2009), "Service orientation: antecedents, outcomes, and implications for hospitality research and practice", *Service Industries Journal*, Vol. 29 No. 10, pp. 1413-1435.

Wang, Y. and Liu, J.H. (2010), "Chaotic particle swarm optimization for assembly sequence planning", *Robotics and Computer-Integrated Manufacturing*, Vol. 26 No. 2, pp. 212-222.

Yee, R.W., Yeung, A.C. and Cheng, T.E. (2010), "An empirical study of employee loyalty, service quality and firm performance in the service industry", *International Journal of Production Economics*, Vol. 124 No. 1, pp. 109-120.

Further reading

Anderson, E.W., Fornell, C. and Lehmann, D.R. (1994), "Customer satisfaction, market share and profitability: findings from Sweden", *Journal of Marketing*, Vol. 58 No. 3, pp. 53-66.

Forrester, J.W. (1961), *Industrial Dynamics*, MIT Press, Cambridge, MA.

Jantti, M., Tanskanen, K. and Kaukola, J. (2009), "Knowledge management challenges in customer support: a case study", *International Conference on Information, Process, and Knowledge Managemente. KNOW'09, IEEE*, pp. 78-83.

Sterman, J.D. (2000), *Busyness Dynamics – Systems Thinking and Modeling for a Complex World*, Vol. 19, Irwin/McGraw-Hill, Boston, MA.

Tustin, E. (1953), *The Mechanism of Economic Systems*, Harvard University Press, Cambridge, MA.

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