A System Dynamics Simulation Model For Scalable-Capacity Manufacturing Systems

Shady S. Elmasry*, Mohamed A. Shalaby*, Mohamed M. Saleh**

* Department of Mechanical Design and Production, Faculty of engineering, Cairo University, Giza 12613, Egypt
**Department of Operations Research & Decision Support, Faculty of Computers and Information, Cairo University, Giza 12613, Egypt
shady23585@yahoo.com, mashalaby@aucegypt.edu, m.saleh@fci-cu.edu.eg

Abstract

This research presents a System Dynamics SD approach to model and analyze a single stage scalable manufacturing system. The system is exposed to a random demand that is assumed to follow a normal distribution pattern. The main contribution in this paper, is adding new modules to the existing state of the art of capacity scalability management in order to bring it near to reality. The proposed modules allow for costs evaluation, scaling capacity on seasonal basis, and applying system breakdowns. A full-fledged simulation model (attached as supplementary material) was developed and tested using Vensim DSS. Two capacity scaling policies are presented and used to study the effect of the new modules on the system's performance - where Capacity level, Inventory level, Backlog level and Costs are the measures of the system's performance. The results show System Dynamics ability to model real conditions that face capacity scaling planners, and present the actual effect of system breakdowns on facility performance. Moreover, this study investigates the impacts of applying seasonal capacity scaling on scalable systems.

Keywords: *Scalable capacity, Manufacturing systems, System Dynamics, Simulation, Breakdowns, Production cost.*

1. Introduction

The history of manufacturing systems shows their evolution over the years as a response to an increasingly dynamic and global market with a greater need for flexibility and responsiveness. Recently, Reconfigurable manufacturing systems (RMS) had been introduced. It is defined as a manufacturing system that evolves its configuration over time in order to provide the functionality and capacity needed, when it is needed (Youssef et al., 2007). RMS is intended to combine the high throughput of dedicated manufacturing line (DML) with the flexibility of flexible manufacturing system (FMS) and react to changes quickly and efficiently (Koren et al, 1999). It allows repeated changes and rearrangements of the components of a manufacturing system in a cost – effective way. The main drawback of RMS is the high investments and high technological requirement needed to implement it.

One of the key features of RMS is capacity scalability. Simply, it is the ability to adjust system capacity to meet variable period-by-period demand. Typical capacity scalability problem addresses when, where and by how much should the capacity of the manufacturing system be scaled to respond to the expected variable demand. Before RMS, Capacity change was limited to capacity expansion only. It was considered a long term investment decision. In RMS, on the other hand, capacity scalability addresses the reduction of capacity besides the expansion as well. Capacity scalability approach in RMS is considered as an operational decision that is able to be executed several times per one year. The challenge that faces scalable manufacturing system is to specify the best capacity scalability policy that satisfies facility objectives with minimum cost.

This paper will contribute to the existing state of the art by introducing new realistic assumptions that help in assessing different scalable policies. A basic model that reflects the state of the art in modeling scalable manufacturing system (Deif & H. ElMaraghy, 2007) is presented first. In order to develop the basic model, three realistic modules are added to it in turn; First module includes a new method to evaluate the cost of implementing different scalable policies which will help in assessing it more precisely. Second module introduces seasonal capacity scaling which is based on scaling capacity every multiple time periods instead of each time period. Third module presents machine breakdown which is considered as a random factor that corrupts implementation of scalable policies. New modules will be analyzed by applying two different scaling policies and comparing their results.

The rest of the paper is assigned as follow: In section 2, literature is reviewed. In section 3, the state of the art basic model is illustrated. In section 4, model refinements beyond the state of the art are explained. In section 5, two scaling policies are applied to analyze refinements. Finally, in section 6 summary and conclusion are stated.

2. Literature review

Capacity scaling is considered a classical problem in many industries, and it was known as the capacity expansion problem to satisfy increasing demand in a cost effective way. The first study of the capacity expansion problem was conducted by Manne (1967). Representative review of the classical capacity expansion problem can be found in Luss (1982). Since demand uncertainty increases and technological advancement are faster, the need to address the capacity scaling problem from a dynamic view point where capacity can be increased and decreased becomes an essential requirement.

Recently, multiple modeling techniques are used to assist the capacity scalability planner to determine the best scalability policy based on different performance measures. Kim and Duffie (2005) presented a multi work station production system model that is based on control theory. A proportional control policy with a control gain K_b delayed by period D_k was applied, and it represents realities of hiring and firing labor force and other issues that prevent instantaneous adjustment of capacity to specify the new capacity. Deif & H. ElMaraghy (2007) proposed a system dynamics approach for a single stage scalable capacity model. The model objective was to examine different scalable policies using multiple performance measures like inventory, backlog and capacity levels. Further analysis for the same capacity scalable model was presented on Deif & H. ElMaraghy (2011) focusing on a market-capacity integration policy. Spicer (2007) developed an integer programming optimization tool to investigate the optimal configuration plan of a scalable RMS. His objective was based on minimizing investment cost and reconfiguration costs over a finite horizon with known demand. Also he presented an optimal solution model for the multi period scalable-RMS using dynamic programming. Asl et al. (2003) presented a multi-period RMS that faces stochastic market demand. He used Markov decision theory supported with feedback control policy to conduct a capacity scaling plan for a finite time horizon. Deif & H. ElMaraghy (2009) developed a system dynamics approach to model and analyzes operational complexity of dynamic capacity in multi-stage production system with stochastic demand. The results of analysis showed that ignoring demand, internal manufacturing delay and capacity scalability delay can lead to wrong decisions concerning both scaling level and backlog management decisions.

Although system breakdowns were not studied for scalable production system, several other studies of traditional systems can be readily applied to the current problem. Breakdowns are characterized by randomness and defined by frequency of breakdowns and time needed to repair. Many researchers assumed different breakdowns behavior. Chakaraborty et al. (2008) introduced a mathematical model for a generalized economic manufacturing quantity for an unreliable production system; he assumed the time to machine breakdown follows Weibull distribution, and proved that preventive maintenance reduces the system cost significantly and determined the optimal production lot size. Gracy et al. (2006) studied an Economic Production Quantity model for a single product subjected to random machine breakdowns that follow an exponential distribution of deterioration, and presented a mathematical model to determine the optimal production uptime that minimizes the expected total cost per unit time. Singa (2010) presented a mathematical model of the production inventory cost functions for systems with breakdowns and without breakdown. He assumed the random number of breakdowns per unit time follows a Poisson distribution and Time-to-breakdown should obey an exponential distribution. A complete solution procedure and a numerical example were conducted to confirm that the optimal run time for the proposed model is obtainable.

Several authors defined few relevant cost items such as scaling cost and physical capacity cost. However, Capacity scaling costs was first introduced by Manne (1961) who presented the physical capacity cost for the new capacity expansion as a typical discounted concave function representing the economy of scale. Deif & W. ElMaraghy (2006 & 2007) added penalty cost which depends on number of rescaling point, and scalability effort cost. There work was directed to produce an optimal capacity scalability plan. Spicer (2007) defined another scaling capacity cost that includes more details as the number of modules sold and bought and used labor cost in the rescaling process. He also added lost capacity cost that represents the lost production opportunity during stoppage and ramp up to the new operational level.

3. The state of the art basic model

The system dynamics model for capacity scaling (Figure 1) illustrates a single stage production system with added refinements (which will be explained later in section 4). In this section, we will focus on the state of the art dynamic representation of the production system that is suitable for capturing the ability to adjust the capacity and, hence, makes the model a valid representation for these systems. The model expresses capacity as a stock level controlled by a scaling rate, the WIP as a stock level controlled by production start rate as an input flow and production rate as an output flow, the Inventory as a stock level controlled by production rate as an input flow and shipment rate as an output flow, and the Backlog as a stock level controlled by order rate as an input flow and shipment rate as an output flow. The model assumes a periodic demand that follows a normal distribution and is known at the beginning of each period, and that production rate equal capacity level at any period t. Basic model nomenclature is shown in Appendix A.

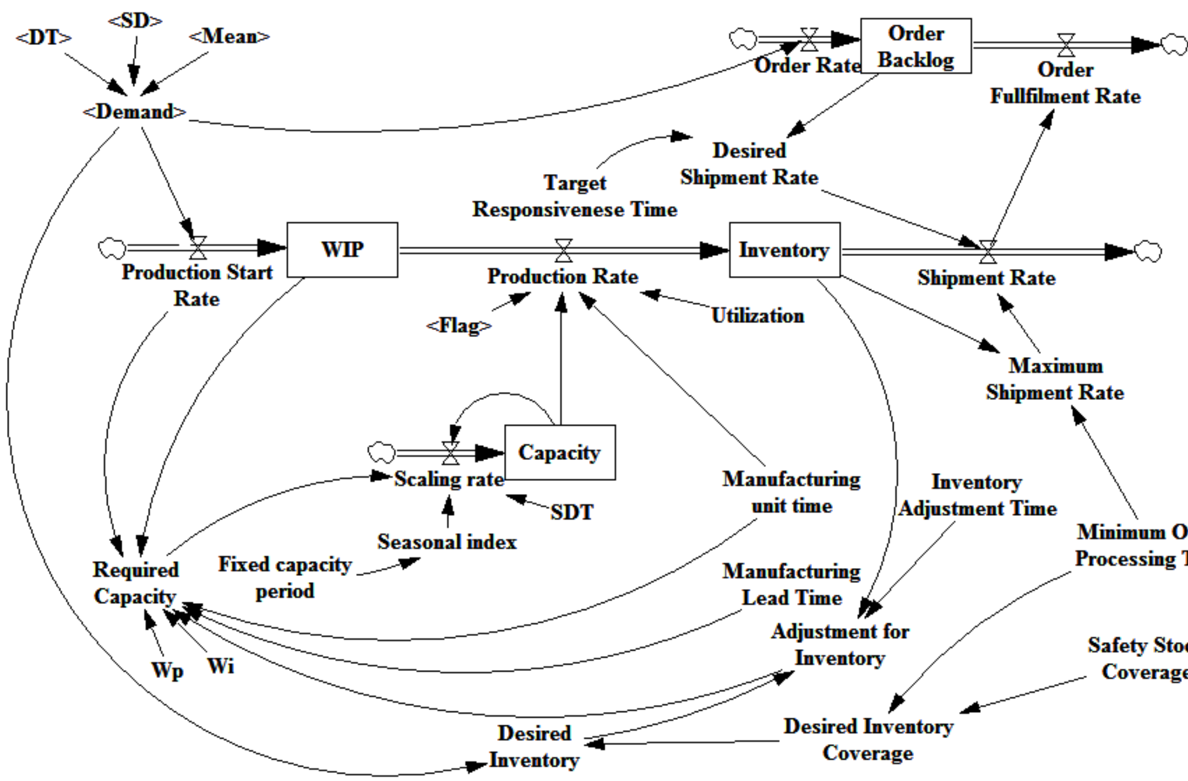


Figure 1: Basic model with refinements

3.1 Basic Model Relationships

The basic model for a scalable manufacturing system as introduced by Deif & H. ElMaraghy (2007) is presented here for brevity. It consists of the following modules; Demand Generation, Capacity Scalability Control, Production Control, Inventory Control, and Order Fulfillment Control. Each module is connected to the others by variables that are common to all modules. They are introduced next:

a- Demand Generation:

In the basic model, periodic demand D(t) is assumed to follow a normal distribution (equation 1). According to Huh et al. (2006), period-by-period demand should have a continuous distribution because demand is inherently continuous, the variance in demand is often high, and finally because continuous demand distribution may generate a more robust capacity plan than finite number of discrete scenarios.

$$\mathrm{D(t)} = \mathrm{AD(t)} + \sqrt[2]{\left[\mathrm{SD}^2 * \frac{2-\mathrm{DT}}{\mathrm{DT}}\right]} * \mathrm{Normal(0,1)} \tag{1}$$

Where DT: time step, SD: standard deviation of demand, AD: average demand.

b- Capacity Scalability Planning and Control:

Capacity scalability decisions are controlled through the scaling rate SR(t) (equation 2).

$$\mathrm{C(t)} = \int_0^{\mathrm{T}} \mathrm{SR(t)} \tag{2}$$

Where T: final time

The equation for the scaling rate SR(t) is determined by the required capacity RC(t) together with the scalability delay time SDT (equation 3).

$$\mathrm{SR(t)} = \frac{\mathrm{RC(t)} - \mathrm{C(t)}}{\mathrm{SDT}} \tag{3}$$

The required capacity RC(t) (equation 4) consist of three components; production start rate PSR(t), adjustment inventory AI(t), and work in process WIP(t) divided by manufacturing lead time MLT. It is defined in this manner to allow implementing different capacity scalability policies based on demand, inventory and WIP levels through manipulating W_P and W_i, where W_p and W_i are constants that represent the weight of these levels considered in capacity computation.

$$\mathrm{RC(t)} = \left[\left(\mathrm{W_p} * \mathrm{PSR(t)}\right) + \left(\mathrm{W_i} * \mathrm{AI(t)}\right) + \left((1 - \mathrm{W_p} - \mathrm{W_i}) * \frac{\mathrm{WIP(t)}}{\mathrm{MLT}}\right)\right] \tag{4}$$

$$\text{where: } 0 \le \mathrm{W_p} \le 1 \text{ and } \mathrm{W_p} + \mathrm{W_i} \le 1.$$

c- Inventory Control:

The inventory control mechanism in the basic model follows the same one introduced by Sterman (2000). The inventory adjustment AI(t) is controlled by determining the gap between desired inventory DI(t) and current inventory I(t) and dividing it by inventory adjustment time IAT (equation 5).

$$\mathrm{AI(t)} = \frac{\mathrm{DI(t)} - \mathrm{I(t)}}{\mathrm{IAT}} \tag{5}$$

The desired inventory DI(t) is assumed to be the result of multiplying the demand D(t) by the desired inventory coverage DIC (equations 6). This formulation ensures enough coverage of products for the anticipated demand. The desired inventory coverage DIC is defined based on two time factors; first is the minimum order processing time MOPT which guarantee maintaining enough coverage to ship at the expected rate. Second is safety stock coverage SSC that ensure an adequate level of service (equation 7).The current inventory level is defined as the accumulation of the difference between production rate PR(t) and shipment rate ShR(t) (equation 8).

$$\mathrm{DI(t) = D(t) * DIC} \tag{6}$$

$$\mathrm{DIC = MOPT + SSC} \tag{7}$$

$$\mathrm{I(t)} = \int_0^{\mathrm{T}} (\mathrm{PR(t)} - \mathrm{ShR(t)}) \tag{8}$$

d- Production Control:

The WIP level is the accumulation of the difference between the production start rate PSR(t) and the actual production rate PR(t) (equation 9).

$$\mathrm{WIP(t)} = \int_0^{\mathrm{T}} (\mathrm{PSR(t)} - \mathrm{PR(t)}) \tag{9}$$

The production start rate PSR(t) is set to be equal to the random demand D(t) (equation 10). The production rate PR(t) is controlled by the capacity scalability level, where it is set equal to capacity level C(t) factored by real system utilization U for practical considerations (equation 11).

$$\mathrm{PSR(t) = D(t)} \tag{10}$$

$$\mathrm{PR(t) = C(t) * U} \tag{11}$$

e- Customer Orders Fulfillment:

Customer orders are fulfilled by the order fulfillment rate OFR(t), which is controlled by the shipment rate ShR(t) (equation 12). The shipment rate is given by the minimum of either the desired shipment rate DSR(t) or the maximum shipment rate MSR(t) (equation 13).

$$\mathrm{OFR(t) = ShR(t)} \tag{12}$$

$$\mathrm{ShR(t) = MIN(DSR(t), MSR(t))} \tag{13}$$

The desired shipment rate DSR(t) is defined as a function of the current backlog B(t) and the target responsiveness time TRT (equation 14).

$$\mathrm{DSR(t)} = \frac{\mathrm{B(t)}}{\mathrm{TRT}} \tag{14}$$

The backlog level is presented as the accumulation of the difference between the order rate OR(t) that have the same value of demand D(t) (equation 15) and the order fulfillment rate OFR(t) (equation 16). In RMS systems, backlog is supposed to be at a low level; practically however, it cannot be zero.

$$\mathrm{OR(t) = D(t)} \tag{15}$$

$$\mathrm{B(t)} = \int_0^{\mathrm{T}} (\mathrm{OR(t)} - \mathrm{OFR(t)}) \tag{16}$$

The maximum shipment rate is determined by the available inventory level I(t) divided by the minimum order processing time MOPT (equation 17).

$$MSR(t) = \frac{I(t)}{MOPT} \tag{17}$$

3.2 Capacity scaling policies

In order to examine the model ability to simulate the real system, two policies will be applied on the presented model. First policy is inventory based policy; it is based on changing the capacity scalability level to adjust production rate to meet the target inventory level (equation 18). This policy showed a perfect performance based on scalability cost. However, it shows a modest performance under cyclic demand scenario (Deif & H. ElMaraghy, 2007). Also it is highly recommended for long life products and low holding cost applications.

$$RC(t) = AI(t) \tag{18}$$

The second policy was introduced by Kim et al. (2005). The capacity scalability mechanism is based on adjusting capacity level to satisfy the previous backlog level factored by a control gain K_b (equation 19). Kim set the K_b = 0.368, where capacity was adjusted without overshoot and with little oscillations.

$$RC(t) = \text{Delay fixed}(B(t),1)*K_b \tag{19}$$

Where, Delay fixed is a function in Vensim DSS.

4. Model refinements beyond the state of the art.

Although the basic scalable capacity model includes many manufacturing system aspects, some performance measures and real conditions in manufacturing systems could not be adopted using it. In order to refine the model to consider these new aspects, additional modules are introduced to the basic model; First module is dedicated to evaluate Production costs which represents an important performance measure for any manufacturing system, second module enhance capacity scaling control to be able to scale capacity on seasonal basis. This is a substantial requirement for industries exposed to specific demand pattern each season; last module simulates manufacturing system breakdowns that cause stoppage of production. Each module is described as follow:

4.1 Production costs

One of the most important performance measures that are required for any decision maker to determine the best decision is the expected costs that results from his decision. Accordingly, a production cost module will be added to the base model. The objective of this module is to help in the assessment of different capacity scaling policies. It involves different manufacturing costs and capacity scaling costs. The criteria of selecting production costs included in the module are the ability to match system planning level. This means that selected costs are neither strategic which is used in production planning for a long period nor operational that is used in accounting daily expenses.

Based on this criterion, the total cost module (Figure 2) is presented as the summation of four main components; Capacity Cost CC(t), Scaling Cost SC(t), Backlog Cost BC(t) and Inventory Cost IC(t). Capacity Cost CC(t) is defined as the cost of producing full capacity at time t. It includes costs of raw material, salaries of workers involved in the production process, overheads, etc. it is formulated as the result of multiplying capacity level C(t) with capacity unit cost CUC (equation 20).

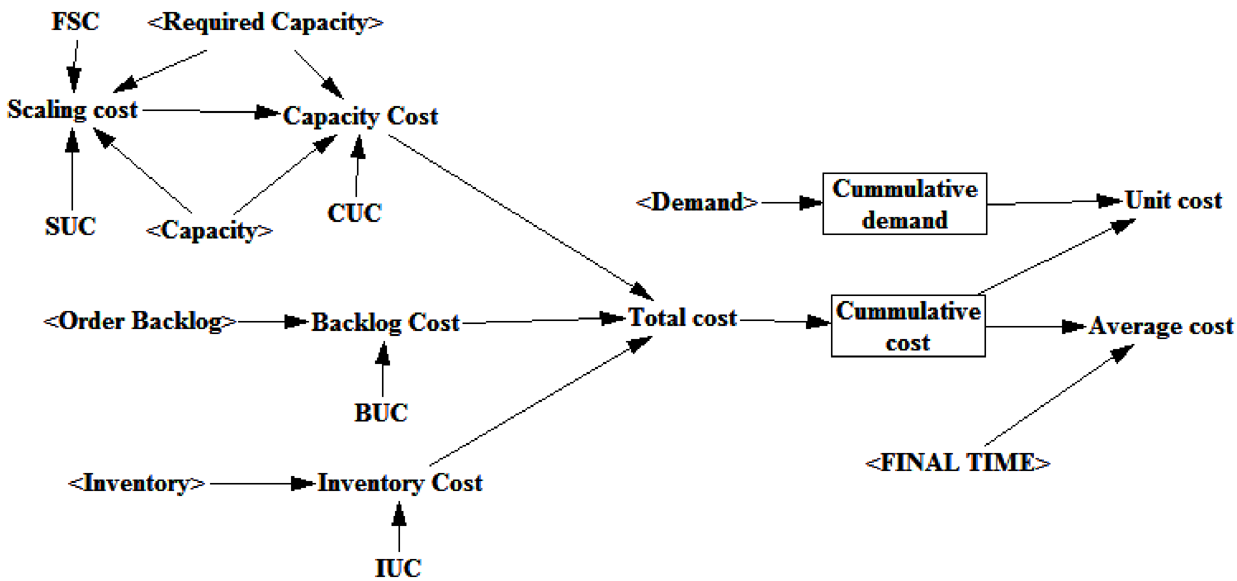


Figure 2: Production Cost module

CC(t) = CUC * C(t) (20)

Where CUC = Capacity unit cost.

The second component evaluates Scaling Costs SC(t) which is composed of two items; first component is a fixed scaling cost FSC that represents overheads of stopping production to rescale capacity, lost production, and fees of labors involved in ordering and estimating new capacity. Fixed scaling cost FSC is assumed to be independent on type of capacity scalability (up or down). Second item is physical scaling costs incurred to increase or decrease capacity levels including adding/removing another spindle to a machine, adding/removing a machine, and new hired or fired workers. Physical scaling cost is assumed to be proportional to the change in capacity. It is assumed that Scaling up unit cost is equal to scaling down unit cost and no outsourcing is allowed.

Here, two conditions may exist; First condition is when capacity level C(t) is **not equal** to the required capacity RC(t); scaling cost SC(t) will be formulated as the difference between required capacity RC(t) and the existing capacity C(t) multiplied by scaling unit cost SUC and added to the fixed scaling cost FSC. Second condition is when capacity level C(t) is **equal** to the required capacity RC(t), scaling cost SC(t) will be equal to zero (equation 21).

$$SC(t) = \begin{cases} SUC * |RC(t) - C(t)| + FSC, & \text{if } RC(t) \neq C(t) \\ 0, & \text{Otherwise} \end{cases} \quad (21)$$

Where SUC = Scaling Unit Cost, FSC = Fixed Scaling Cost

The third component is inventory cost IC(t) which represent cost of holding goods in stock. It includes ware housing depreciation, insurance, taxation, obsolescence and shrinkage cost at time t. Inventory cost is directly proportional to inventory level I(t) (equation 22).

$$IC(t) = IUC * I(t) \quad (22)$$

Where IUC = Inventory unit cost.

The forth component is backlog cost BC(t) which reflect penalties of late delivery costs. It is simply presented as backlog level B(t) multiplied by backlog unit cost BUC (equation 23).

$$BC(t) = BUC * B(t) \quad (23)$$

Where BUC = Backlog unit cost.

Total costs TC(t) are deduced by summation of capacity, scaling, backlog, and inventory costs (equation 24) at each time period. In order to calculate the average cost for any time horizon, new stock for storing and adding total costs is introduced as Cumulative cost. It is formulated to integrate total costs until the final time (equation 25). Consequently, the average total cost is determined by dividing cumulative cost by the final time (equation 26). To compare between policies with different time horizons, the unit cost measurement is required. The cumulative cost is divided by the cumulative demand (equation 27, 28).

$$TC(t) = CC(t) + SC(t) + BC(t) + IC(t) \quad (24)$$

$$\text{Cummulative cost} = \int_0^T TC(t) \quad (25)$$

$$\text{Average cost} = (\text{Cumulative cost}) / T \quad (26)$$

$$\text{Cumulative demand} = \int_0^T D(t) \quad (27)$$

$$\text{Unit cost} = (\text{Cumulative cost}) / (\text{Cumulative demand}) \quad (28)$$

4.2 Seasonal capacity scaling

One of the most disturbing problems in the basic model is the need to readjust capacity each time period. This issue requires high efforts and costs to achieve it. However, if we investigate the real life we will find many industries characterized by having a certain period-by period demand within a specific season. For these industries there is no need to rescale capacity level each time period. Otherwise, capacity planning takes place on quarterly (every three months) or seasonal basis while demand is updated period-by-period. According to this new approach, capacity scaling mechanism that was introduced in the basic model will be modified to be adapted with seasonal capacity scaling.

Seasonal capacity scaling is based on maintaining capacity at a constant level for a fixed number of periods or a season, while demand remains periodic. At the end of season, capacity will be rescaled according to the average demand of the following season. New variables will be added to the basic model to achieve this property. These variables are responsible to define number of periods that represent the season and to prevent capacity scaling within season periods.

This logic is implemented to the model through adding fixed scaling period FSP and seasonal index SI (Figure 3); Fixed Scaling Period is defined as the number of periods per one season, and Seasonal Index SI present a pulse function that allows capacity scaling only at the beginning of a season and blocks capacity scaling within the season (equation 29&30). For simplicity, the value of the seasonal capacity will be taken as the demand value for the starting period in the season. However, different scaling policies may easily apply different assumptions to select the new capacity used for the new season.

SI(t) = PULSE TRAIN (FSP, 0, FSP, Final time) (29)

$$SR(t) = (RC(t) - C(t)) * SI(t) / SDT \tag{30}$$

Where: PULSE TRAIN is a function in Vensim DSS

SDT= Scalability Delay Time

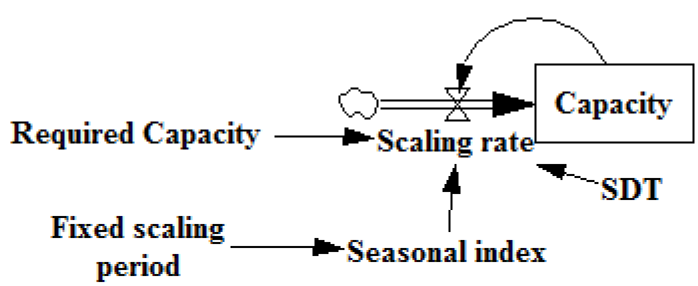


Figure 3: Seasonal capacity scaling module

4.3 System breakdown

System breakdowns are considered an operational phenomenon that highly influences a production process. It affect capacity planning deeply especially when it shifts from an in control state to out of control state in a random pattern. In this situation, a capacity scaling decision may be inferred to overcome the impact of breakdown on the production process. In order to handle the problem of introducing system breakdowns in to the manufacturing system, a new module is added to the basic model.

Proposed module includes two main variables; first is the frequency of breakdowns which are assumed to be a random variable that follows a uniform distribution, and is represented in the model as the uptime duration. Second is the time lost during system breakdown which is assumed a random variable that follows a normal distribution, and is represented in the model as down time duration (Chakraborty, 2008). To simplify breakdown module, Breakdown occurrence is assumed to stop the production process.

Model handling of breakdowns is based on identifying a Flag which indicate production system status whether it is on uptime or downtime. When Flag has a value of one, this means that production system is in uptime. While when flag have a value of zero, this means that breakdown exists. This mechanism is accomplished by introducing new parameters and relations (equation 31-36). Flag is defined in a separate module (Figure 4) and is added to the basic model.

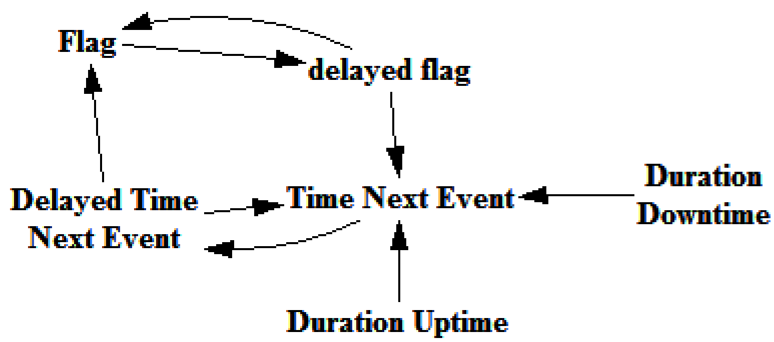


Fig (4): System breakdown module

DUT= Random uniform ($\overline{X}$, σ) (31)

DDT= Random normal (Min, Max, $\overline{X}$, σ) (32)

DF= Delay fixed (Flag, DT, 0) (33)

DTNE= Delay fixed (TNE, DT, 0) (34)

$$TNE= \begin{cases} DTNE, & t<DTNE \\ t + DDT, & DF>0 \\ t + DUT, & \text{otherwise} \end{cases} \quad (35)$$

$$Flag= \begin{cases} DF, & t < DTNE \\ 1- DF, & \text{Otherwise} \end{cases} \quad (36)$$

- DUT (Duration up time): uptime period of manufacturing system.
- DDT (Duration downtime): downtime period of manufacturing system.
- DF (Delayed flag): flag value delayed by time step.
- Flag: variable that indicate system situation (if uptime or down time).
- TNE (Time next event): time of the next uptime or downtime.
- DTNE (Delayed time next event): time of the next uptime or downtime delayed by specific period.
- $\overline{X}$, σ: average value and standard deviation of the distribution.
- DT: time step.

The reader may refer to the breakdown module attached in the supplementary material.

5. Policy analysis

In order to investigate the dynamic behavior and performance for the new modules added to the basic model, two different policies will be used for analysis; Inventory based policy and Kim policy. Capacity level, Inventory level, Backlog level and Total cost are considered the performance measures of the system. These measures are selected to reflect system stability, responsiveness and expected cost. The analysis will be executed on two steps; first is by adding seasonal capacity scaling and production cost modules to the basic model, while the second is by adding system breakdowns and production cost modules to the basic model. The reason behind separating seasonal capacity scaling and machine breakdown is to examine the effect of each of them on the system independently. This will ensure more insight for the assessment of each module. The model is constructed and analyzed using Vensim DSS package.

The model will be initialized at equilibrium table 1 (i.e. the initial values of the WIP, capacity, inventory and backlog levels are set to the target values (Sterman, 2000)) and simulated for 100 month. The selected values for the different time parameters are based on a case study of make-to-order furniture manufacturing company (Deif & H. ElMaraghy, 2007).

Table 1: Model initial conditions

Parameter	Value	Unit	Parameter	Value	Unit
Average demand (AD)	10,000	Parts	Utilization Level (U)	100%	-
Demand Standard Deviation (SD)	1,000	Month	Target Responsiveness Time (TRT)	1	Month
Manufacturing Lead Time (MLT)	1	Month	Inventory weight (W_i)	0	-
Inventory Adjustment Time (IAT)	2	Month	Demand weight (W_p)	1	-
Minimum Order Processing Time (MOPT)	1	Month	Scalability Delay time (SDT)	1	Month
Safety Stock Coverage (SSC)	2	Month	CUC, IUC and BUC	50	pound

5.1 Seasonal capacity scaling and production cost

Figure 5 (a-d) shows the response of performance measures assuming a season of 3 periods (SI=3) while applying Inventory based policy and Kim policy. System response for any performance measure will be considered stable if its pattern oscillates around a fixed average value (average value is constant along the time horizon). The results show a stable response for capacity, inventory, backlog and total cost in both policies. But variability in total cost and backlog response was higher than that in capacity and inventory response for both policies. The reason of higher variations is due to fixing capacity level within a season regardless of demand variations. Consequently, backlog and total cost are accumulated at higher levels. This performance advocates that using seasonal capacity scaling is more preferred than periodic scaling from system stability point of view.

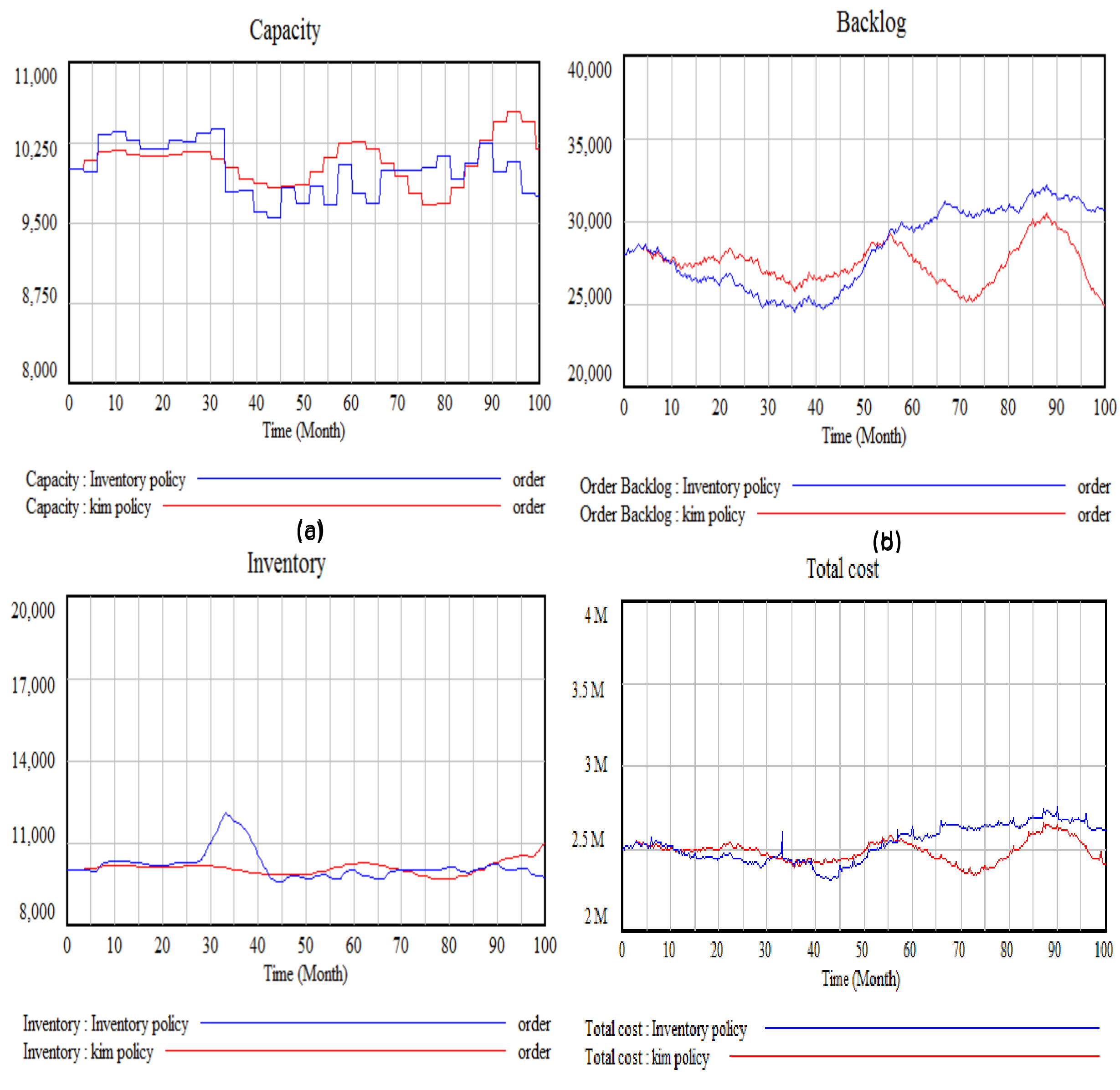


Figure 5: Dynamic Response for Different measures in case of seasonal capacity scaling

5.2 System breakdowns and production costs

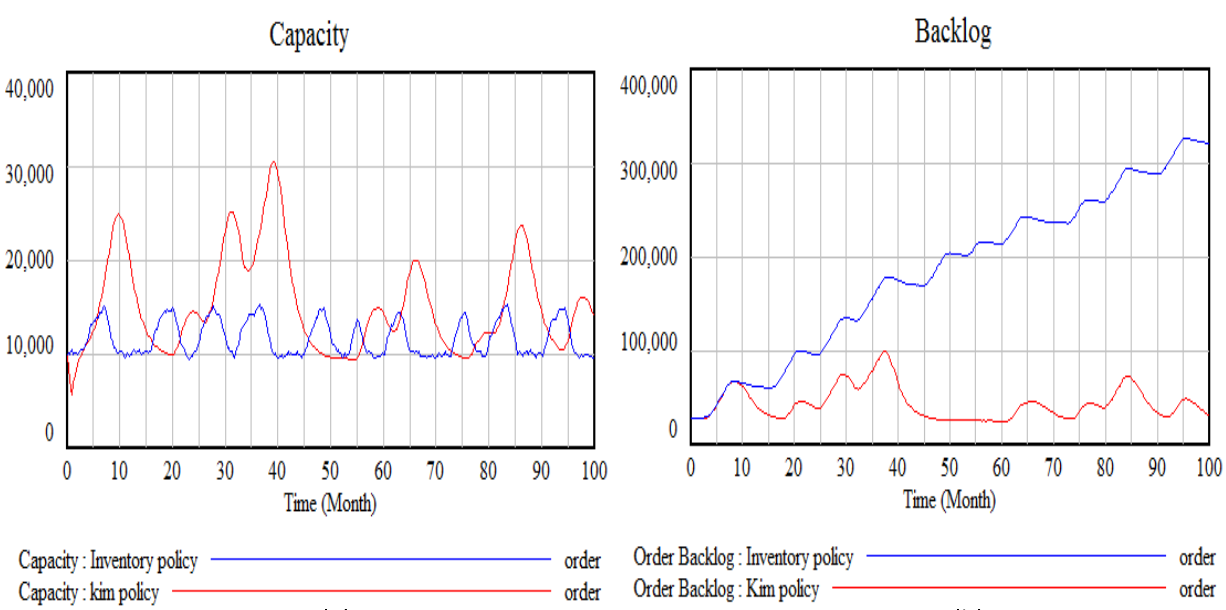
System breakdowns module is connected to the basic model through a Flag that is multiplied by the production rate PR (equation 37). Duration uptime DUT and duration downtime DDT are computed according to equations (38 & 39). Figure 6 (a-d) illustrates the effect of system breakdowns on different performance measures. As shown in figure 6 (b & d) breakdowns cause a great disturbance (blowing up) in backlog and total cost response for Inventory based policy. This occurred due to low values of inventory and capacity levels provided in this policy, where inventory level reaches zero value several times along the time horizon, figure 6 (c). On the other hand, figure 6 (a-c) shows high variations in the response of capacity, backlog, inventory, and total cost for Kim policy; where all these responses highly oscillate around their average value.

$$PR(t) = C(t) * U * Flag \quad (37)$$

DUT= Random uniform (1, 7, 0) (38)

DDT= Random normal (1, 7, 4, 1, 0) (39)

In general, system breakdowns lead to random performance for all variables considered in both policies. This was expected due to the random nature of breakdown proposed in this work. In future work to face this problem the model structure needs to be modified and new scaling policies have to be developed.



(a) (b)

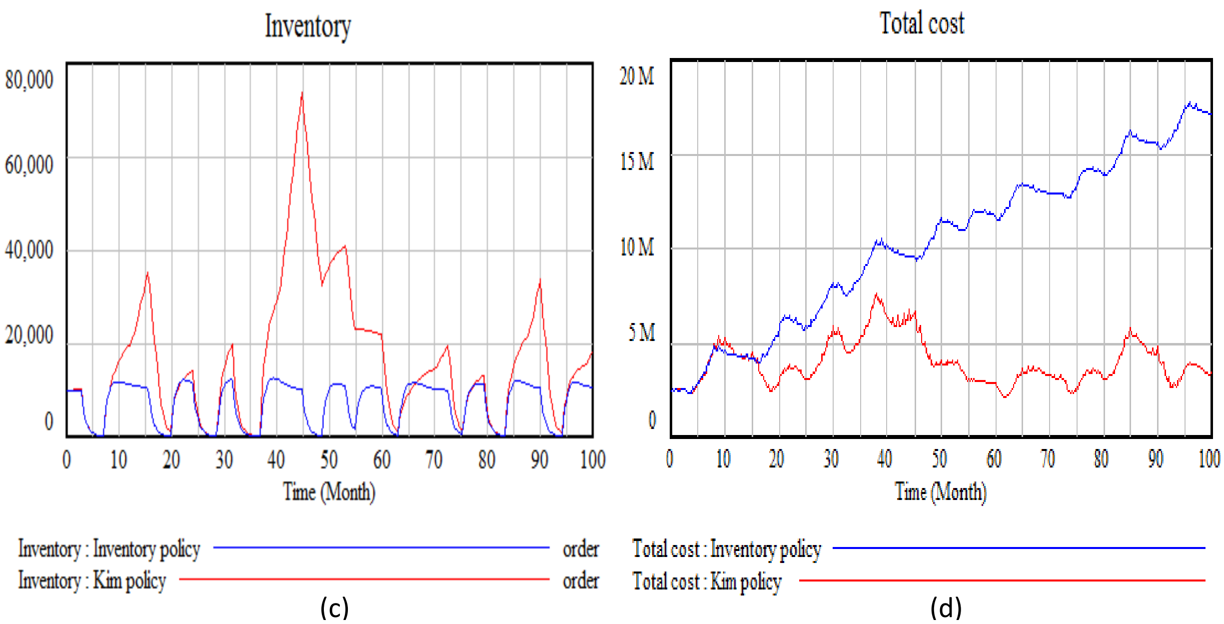


Figure 6: Dynamic Response for Different measures in case of machine breakdowns

6. Summary, conclusion and future work

This paper presented a model for a manufacturing system that is characterized by capacity scalability. Modeling was based on a system dynamics approach to better reflect the dynamic nature of capacity scalability process. The paper contributes to the knowledge of capacity scalability management by adding new refinements to the existing state of the art. The new refinements include adding production costs estimation, scaling capacity on seasonal basis and adopting system breakdowns. Each of these refinements was defined and introduced to the scalable model in the form of module. Multiple performance measures including capacity level, inventory level, backlog level and total production costs were selected for analysis and assessment of the new refinements. Two capacity scaling policies were used to illustrate and analyze the effect of the new refinements on the basic model performance. The main conclusions of the conducted analysis are:

- Systems Dynamics is a viable approach to model traditional as well as manufacturing systems with scalable-capacity.
- A diversity of cost schemes and realistic assumptions such as Seasonal capacity scaling, equipment breakdowns, and variable production capacity decisions can be successfully modeled. Total cost can be used as an objective criterion to compare different scaling policies.
- Seasonal capacity scaling is an important approach in scalable systems that lead to more stable systems and decreases scaling cost deeply.

Possible future research directions are:

- Traditional optimal search and parametric analysis methods can be devised to optimize the system's performance and select best capacity planning policies.
- More suitable scaling policies need to be developed to avoid the unstable effect of system breakdowns.

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Appendix A

Basic Model nomenclature:

C = Capacity level at time t.

B = Backlog level at time t.

I = Inventory level at time t.

WIP = WIP level at time t.

PR = Production rate at time t.

PSR = Production start rate at time t.

AD = Average demand.

SD = Standard deviation for the normal demand distribution.

DT = Time step.

OR = Order rate at time t.

ShR = Shipment rate at time t.

OFR = Order fulfillment rate at time t.

TRT = Target responsiveness time.

DSR = Desired shipment rate at time t.

MSR = Maximum shipment rate at time t.

MOPT = Minimum order processing time.

SSC = Safety stock coverage time.

DIC = Desired inventory coverage time.

IAT = Inventory adjustment time.

I = Desired inventory level at time t.

AI = Adjustment for inventory rate at time t.

U = Utilization level of the available capacity.

RC = Required capacity at time t.

SDT = Scalability delay time.

SR = Scalability rate at time t.

MLT = Manufacturing lead time.

MUT = Manufacturing unit time.

W_i = The relative weight of inventory consideration in capacity scalability decision.

W_p = The relative weight of demand consideration in capacity scalability decision.