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Receding Horizon Control on Large Scale Production/Distribution/Inventory Network

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***Abstract*—Receding horizon control (RHC) has now become a standard control methodology for industrial and process systems. As supply chains can be operated sequentially, i.e., stages update their policies in series, synchronously, In this paper, two method for locally receding horizon controllers applied to a supply chain management system consist of one plant, two warehouses ,four distribution centers and four retailers. By this implementation, As supply chains can be operated sequentially, i.e., stages update their policies in series, synchronously, each node by a decentralized receding horizon controller optimizes locally for its own policy, and communicates the most recent policy to those nodes to which it is coupled. Also a move suppression term added to cost function, that increased system robustness toward changes on demands.**

***Index Terms*—Receding horizon control, Supply chain management, Demand, Move suppression.**

I. INTRODUCTION

A supply chain is a network of facilities and distribution entities (suppliers, manufacturers, distributors, retailers) that performs the functions of procurement of raw materials, transformation of raw materials into intermediate and finished products and distribution of finished products to customers. Between interconnected entities, there are two types of process flows: information flows, e.g., an order requesting goods, and material flows, i.e., the actual shipment of goods (Figure 1). Key elements to an efficient supply chain are accurate pinpointing of process flows and timing of supply needs at each entity, both of which enable entities to request items as they are needed, thereby reducing safety stock levels to free space and capital. The operational planning and direct control of the network can in principle be addressed by a variety of methods, including deterministic analytical models, stochastic analytical models, and simulation models, coupled with the desired optimization objectives and network performance measures [1].

The merit of receding horizon control is its applications in multivariable control in the presence of constraints. The success of receding horizon control is due to the fact that it is perhaps the most general way of posing the control problem in the time domain. The use a finite horizon strategy allows the explicit handling of process and operational constraints by the receding horizon control [2]. In a recent paper [3], a receding horizon control strategy was employed for the optimization of production/ distribution systems, including a simplified scheduling model for the manufacturing function. The suggested control strategy considers only deterministic type of demand, which reduces the need for an inventory control mechanism [4,5].

For the purposes of our study and the time scales of interest, a discrete time difference model is developed [6]. The model is applicable to multi echelon supply chain networks of arbitrary structure. To treat process uncertainty within the deterministic supply chain network model, a receding horizon control approach is suggested [7,8].

Typically, receding horizon control is implemented in a centralized fashion [7]. The complete system is modeled, and all the control inputs are computed in one optimization problem. In large scale applications, such as power systems, water distribution systems, traffic systems, manufacturing systems, and economic systems, such a centralized control scheme may not suitable or even possible for technical or commercial reasons [8,9], it is useful to have distributed or decentralized control schemes, where local control inputs are computed using local measurements and reduced order models of the local dynamics. The algorithm uses a receding horizon, to allow the incorporation of past and present control actions to future predictions [10,11]. As well as, further decentralized receding horizon control advantages are less computational complication and lower error risk [12,13].

So As supply chains can be operated sequentially, locally Consecutive receding horizon controllers to a supply chain management system consist of one plant, two warehouses, four distribution centers and four retailers. Also a move suppression term add to cost function, that increase system robustness toward changes on demands. Through illustrative simulations, it is demonstrated that the model can accommodate supply chain networks of realistic size under disturbances.

II. RECEDING HORIZON CONTROL FOR MULTI ECHELON SUPPLY CHAIN MANAGEMENT SYSTEM

Supply chains are complicated dynamical systems triggered by customer demands. Over the past decade, supply chain management and control has become a strategic focus of leading manufacturing companies. This has been caused by rapid changes in environments in which the companies

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operate, characterized by high globalization of markets and ever increasing customer demands for higher levels of service and quality. Proper selection of equipment, machinery, buildings and transportation fleets is a key component for the success of such systems. However, efficiency of supply chains mostly depends on management decisions, which are often based on intuition and experience. Due to the increasing complexity of supply chain systems (which is the result of changes in customer preferences, the globalization of the economy and the stringy competition among companies), these decisions are often far from optimum. Another factor that causes difficulties in decision making is that different stages in supply chains are often supervised by different groups of people with different managing philosophies. From the early 1950s it became evident that a rigorous framework for analyzing the dynamics of supply chains and taking proper decisions could improve substantially the performance of the systems. Due to the resemblance of supply chains to engineering dynamical systems, control theory has provided a solid background for building such a framework. During the last half century many mathematical tools emerging from the control literature have been applied to the supply chain management problem. These tools vary from classical transfer function analysis to highly sophisticated control methodologies, such as receding horizon control and neuro dynamic programming [9].

In this work, a discrete time difference model is developed [4]. The model is applicable to multi echelon supply chain networks of arbitrary structure, that *DP* denote the set of desired products in the supply Chain and these can be manufactured at plants, *P*, by utilizing various resources, *RS*. The manufacturing function considers independent production lines for the distributed products. The products are subsequently transported to and stored at warehouses, *W*. Products from warehouses are transported upon customer demand, either to distribution centers, *D*, or directly to retailers, *R*. Retailers receive time varying orders from different customers for different products. Satisfaction of customer demand is the primary target in the supply chain management mechanism. Unsatisfied demand is recorded as backorders for the next time period. A discrete time difference model is used for description of the supply chain dynamic characteristics of the network. As a result, dynamics of higher frequency than that of the selected time scale are considered negligible and completely attenuated by the network [4,14].

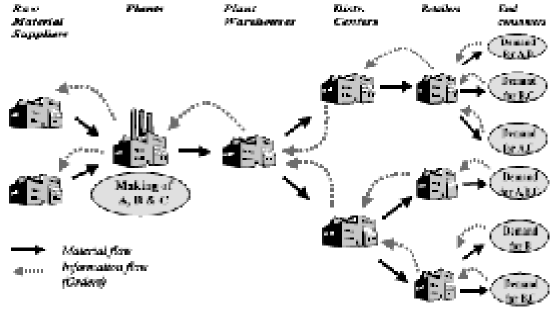

Figure 1. Schematic of a multi echelon/multi product (A, B, C) supply chain network with process flows.

Network dynamics. It is assumed that decisions are taken within equally spaced time periods (e.g. hours, days, or weeks). The duration of the base time period depends on the

Plants *P*, warehouses *W*, distribution centers *D*, and retailers *R* constitute the nodes of the system. For each node, *k*, there is a set of upstream nodes and a set of downstream nodes, indexed by (k', k''). Upstream nodes can supply node *k* and downstream nodes can be supplied by *k*. All valid (k', k) and/or (k, k'') pairs constitute permissible routes within the network. All variables in the supply chain network (e.g. inventory, transportation loads) valid for bulk commodities and products. For unit products, continuous variables can still be utilized, with the addition of a post-processing rounding step to identify neighbouring integer solutions. This approach, though clearly not formally optimal, may be necessary to retain computational tractability in systems of industrial relevance.

A product balance around any network node involves the inventory level in the node at time instances t and $t-1$, as well as the total inflow of products from upstream nodes and total outflow to downstream nodes. The following balance equation is valid for nodes that are either warehouses or distribution centers:

$$y_{i,k}(t) = y_{i,k}(t-1) + \sum_{k'} x_{i,k',k}(t-L_{k',k}) - \sum_{k''} x_{i,k,k''}(t), \qquad (1)$$
$$\forall k \in \{W, D\}, \qquad t \in T, \qquad i \in DP$$

where $y_{i,k}$ is the inventory of product i stored in node k; $x_{i,k',k}$ denotes the amount of the i-th product transported through route (k', k); $L_{k',k}$ denotes the transportation lag (delay time) for route (k', k), i.e. the required time periods for the transfer of material from the supplying node to the current node. The transportation lag is assumed to be an integer multiple of the base time period.

For retailer nodes, the inventory balance is slightly modified to account for the actual delivery of the i-th product attained, denoted by $d_{i,k}(t)$.

$$y_{i,k}(t) = y_{i,k}(t-1) + \sum_{k'} x_{i,k',k}(t-L_{k',k}) - d_{i,k}(t), \qquad (2)$$
$$\forall k \in \{R\}, \qquad t \in T, \qquad i \in DP.$$

The amount of unsatisfied demand is recorded as backorders for each product and time period. Hence, the balance equation for back orders takes the following form:

$$BO_{i,k}(t) = BO_{i,k}(t-1) + R_{i,k}(t) - d_{i,k}(t) - LO_{i,k}(t), \qquad (3)$$
$$\forall k \in \{R\}, \qquad t \in T, \qquad i \in DP.$$

where $R_{i,k}$ denotes the demand for the i-th product at the k-th retailer node and time period t. $LO_{i,k}$ denotes the amount of cancelled back orders (lost orders) because the network failed to satisfy them within a reasonable time limit. Lost orders are usually expressed as a percentage of unsatisfied demand at time *t*. Note that the model does not require a separate balance for customer orders at nodes other than the final retailer nodes[4,15].

Receding horizon control is a model based control strategy that calculates at each sampling time via optimization the optimal control action to maintain the output of the plant close to the desired reference. In fact, receding horizon control stands for a family of methods that select control actions based on online optimization of an objective function. receding horizon control has gained wide acceptance in the chemical and other process industries as the basis for advanced multivariable control schemes. In receding horizon control, a system model and current and historical measurements of the process are used to predict the system behavior at future time instants. A control relevant objective function is then optimized to calculate a sequence of future control moves that must satisfy system constraints. The first predicted control move is implemented and at the next sampling time the calculations are repeated using updated system states (illustrated in Figure 2). Receding horizon control represents a general framework for control system implementation that accomplishes both feedback and feed forward control action on a dynamical system. The appeal of receding horizon control over traditional approaches to control design include (1) the ability to handle large multivariable problems, (2) the explicit handling of constraints on system input and output variables, and (3) its relative ease of use. Receding horizon control applied to supply chain management relies on dynamical models of material flow to predict inventory changes among the various nodes of the supply chain. These model predictions are used to adjust current and future order quantities requested from upstream nodes such that inventory will reach the targets necessary to satisfy demand in a timely manner [16]. The control system aims at operating the supply chain at the optimal point despite the influence of demand changes [12,13]. The control system is required to possess built in capabilities to recognize the optimal operating policy through meaningful and descriptive cost performance indicators and mechanisms to successfully alleviate the detrimental effects of demand uncertainty and variability. The main objectives of the control strategy for the supply chain network can be summarized as follows: (i) maximize customer satisfaction, and (ii) minimize supply chain operating costs.

The first target can be attained by the minimization of back orders (i.e. unsatisfied demand) over a time period because unsatisfied demand would have a strong impact on company reputation and subsequently on future demand and total revenues. The second goal can be achieved by the minimization of the operating costs that include transportation and inventory costs that can be further divided into storage costs and inventory assets in the supply chain network. Based on the fact that past and present control actions affect the future response of the system, a receding time horizon is selected. Over the specified time horizon the future behavior of the supply chain is predicted using the described difference model (Eqs. (1)–(3)). In this model, the state variables are the product inventory levels at the storage nodes, *y*, and the back orders, *BO*, at the order receiving nodes. The manipulated (control or decision) variables are the product quantities transferred through the network's permissible routes, *x*, and the delivered amounts to customers, *d*. Finally, the product back orders, *BO*, are also matched to the output variables. The inventory target levels (e.g. inventory setpoints) are time invariant parameters. The control actions that minimise a performance index associated with the outlined control objectives are then calculated over the receding time horizon. At each time period the first control action in the calculated sequence is implemented. The effect of unmeasured demand disturbances and model mismatch is computed through comparison of the actual current demand value and the prediction from a stochastic disturbance model for the demand variability. The difference that describes the overall demand uncertainty and system variability is fed back into the receding horizon control scheme at each time period facilitating the corrective action that is required.

The centralized mathematical formulation of the performance index considering simultaneously back orders, transportation and inventory costs takes the following form [4]:

$$
\begin{aligned}
J_{total} = & \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (4) \\
& \sum_{t}^{t+P} \sum_{k\in\{W,D,R\}} \sum_{i\in DP} \left\{ w_{y,i,k} (y_{i,k}(t) - y_{s,i,k}(t))^2 \right\} \\
& + \sum_{t}^{t+M} \sum_{k\in\{W,D,R\}} \sum_{i\in DP} \left\{ w_{x,i,k',k} (x_{i,k',k}(t))^2 \right\} \\
& + \sum_{t}^{t+P} \sum_{k\in\{R\}} \sum_{i\in DP} \left\{ w_{BO,i,k} (BO_{i,k}(t))^2 \right\} \\
& + \sum_{t}^{t+M} \sum_{k\in\{W,D,R\}} \sum_{i\in DP} \left\{ w_{\Delta x,i,k',k} (x_{i,k',k}(t) - x_{i,k',k}(t-1))^2 \right\}
\end{aligned}
$$

The performance index, *J*, in compliance with the outlined control objectives consists of four quadratic terms. Two terms account for inventory and transportation costs throughout the supply chain over the specified prediction and control horizons(P , M). A term penalizes back orders for all products at all order receiving nodes (e.g. retailers) over the prediction horizon P. Also a term penalizes deviations for the decision variables (i.e. transported product quantities) from the corresponding value in the previous time period over the control horizon M. The term is equivalent to a penalty on the rate of change in the manipulated variables and can be viewed as a move suppression term for the control system. Such a policy tends to eliminate abrupt and aggressive control actions and subsequently, safeguard the network from saturation and undesired excessive variability induced by sudden demand changes. In addition, transportation activities are usually preferred to resume a somewhat constant level rather than fluctuate from one time period to another.

However, the move suppression term would definitely affect control performance leading to a more sluggish dynamic response. The weighting factors, $w_{y,i,k}$, reflect the inventory storage costs and inventory assets per unit product, $w_{x,i,k',k}$, account for the transportation cost per unit product for route (k',k) .Weights $w_{BO,i,k}$ correspond to the penalty imposed on unsatisfied demand and are estimated based on the impact service level has on the company reputation and future demand. Weights $w_{\Delta x,i,k',k}$, are associated with the penalty on the rate of change for the transferred amount of the i-th product through route (k',k). Even though, factors $w_{y,i,k}$, $w_{x,i,k',k}$ and $w_{BO,i,k}$ are cost related that can be estimated with a relatively good accuracy, factors $w_{\Delta x,i,k',k}$ are judged and selected mainly on grounds of desirable achieved performance.

The weighting factors in cost function also reflect the relative importance between the controlled (back orders and inventories) and manipulated (transported products) variables. Note that the performance index of cost function reflects the implicit assumption of a constant profit margin for each product or product family. As a result, production costs and revenues are not included in the index.

But in this paper, a consecutive decentralized formulation will used, namely centralized cost function divided to decentralized cost functions for each stage(warehouse, distribution center, retailer):

$$\begin{aligned} J_1 = {} & \sum_{t}^{t+P}\sum_{i\in DP}\left\{w_{y,i,k}(y_{i,k}(t))^2\right\} \\ & + \sum_{t}^{t+M}\sum_{i\in DP}\left\{w_{x,i,k',k}(x_{i,k',k}(t))^2\right\} \\ & + \sum_{t}^{t+M}\sum_{i\in DP}\left\{w_{\Delta x,i,k',k}(x_{i,k',k}(t)-x_{i,k',k}(t-1))^2\right\}, \quad k\in W \end{aligned} \tag{5}$$

$$\begin{aligned} J_2 = {} & \sum_{t}^{t+P}\sum_{i\in DP}\left\{w_{y,i,k}(y_{i,k}(t))^2\right\} \\ & + \sum_{t}^{t+M}\sum_{i\in DP}\left\{w_{x,i,k',k}(x_{i,k',k}(t))^2\right\} \\ & + \sum_{t}^{t+M}\sum_{i\in DP}\left\{w_{\Delta x,i,k',k}(x_{i,k',k}(t)-x_{i,k',k}(t-1))^2\right\}, \quad k\in D \end{aligned} \tag{6}$$

$$\begin{aligned} J_3 = {} & \sum_{t}^{t+P}\sum_{i\in DP}\left\{w_{y,i,k}(y_{i,k}(t))^2\right\} \\ & + \sum_{t}^{t+M}\sum_{i\in DP}\left\{w_{x,i,k',k}(x_{i,k',k}(t))^2\right\} \\ & + \sum_{t}^{t+P}\sum_{i\in DP}\left\{w_{BO,i,k}(BO_{i,k}(t))^2\right\} \\ & + \sum_{t}^{t+M}\sum_{i\in DP}\left\{w_{\Delta x,i,k',k}(x_{i,k',k}(t)-x_{i,k',k}(t-1))^2\right\}, \quad k\in R. \end{aligned} \tag{7}$$

Therefore by this implementation, As supply chains can be operated sequentially, i.e., stages update their policies in series, synchronously, each node by a decentralized receding horizon controller optimizes locally for its own policy, and communicates the most recent policy to those nodes to which it is coupled. In fact, receding horizon controllers of retailers (with Eqs. (1),(5)) only will optimized locally for its own policy and then will sent its optimal inputs to upstream joint nodes to those nodes which it is coupled (distribution centers), as measurable disturbances. Also receding horizon controllers of distribution centers (with Eqs. (1),(6)) only will optimized locally for its own policy and then will sent its optimal inputs to upstream joint nodes to those nodes which it is coupled (warehouse centers), as measurable disturbances. Finally, receding horizon controllers of warehouses (with Eqs. (2),(3),(7)) will optimized locally for its own optimal inputs.

Two types of sequential decentralized receding horizon control can be used. In first method, each node completely by a decentralized receding horizon control optimizes locally for its own policy. At each time period, the first decentralized receding horizon control action in the calculated sequence is implemented until receding horizon control process complete. In fact, decentralized receding horizon controllers corresponding to retailers will done locally for regulating inventory level in R and then will sent its receding horizon control optimal inputs at long prediction horizon to upstream joint nodes to those nodes which it is coupled (distribution centers), as measurable disturbances. Also receding horizon controllers corresponding to distribution centers will optimized locally and then will sent its optimal inputs to upstream joint nodes to those nodes which it is coupled (warehouse centers), as measurable disturbances. Finally, receding horizon controllers corresponding to warehouses will optimized locally for its own optimal inputs. In fact decentralized receding horizon controllers, sequentially operate (Figure 2).

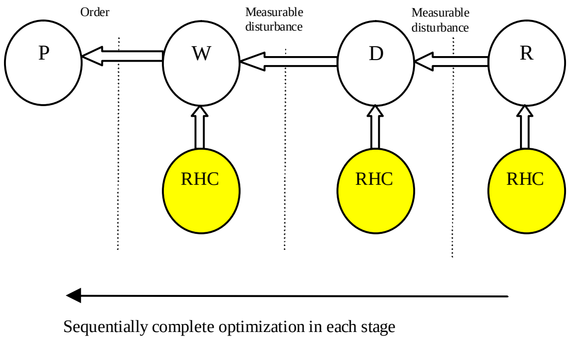

Figure 2. Procedure of first consecutive decentralized RHC

But in second method, decentralized receding horizon controllers in each stage are updated in each time period and the first control action in the calculated sequence is implemented, and this procedure for next time periods is continued (Figure 3).

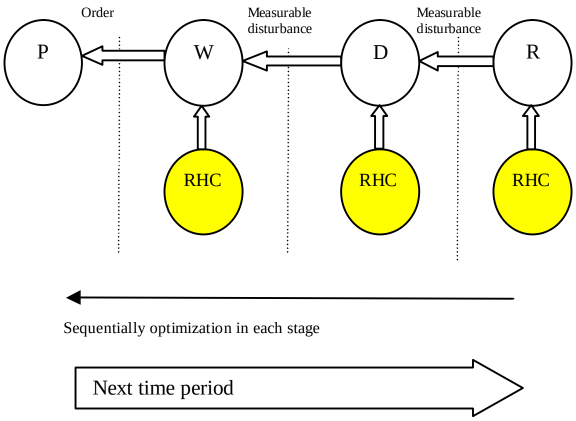

Figure 3. Procedure of second consecutive decentralized RHC

III. SIMULATIONS

A four echelon supply chain system is used in the simulated examples. The supply chain network consists of one production nodes, two warehouse nodes, four distribution centers, and four retailer nodes (Figure 4). All possible connections between immediately successive echelons are permitted. One product family consist of 12 products is being distributed through the network. Inventory setpoints, maximum storage capacities at every node, and transportation cost data for each supplying route are reported in Table 1.

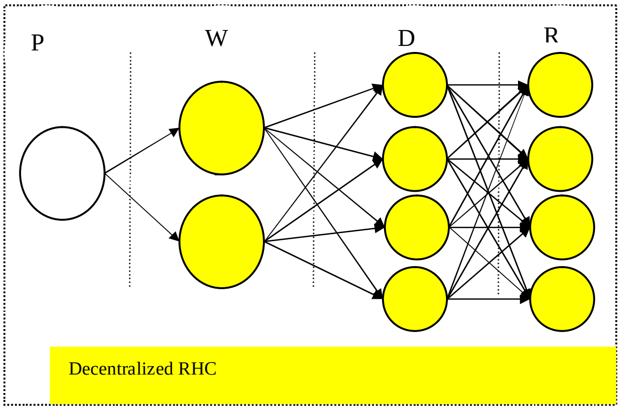

Figure 4. Receding horizon control framework in a multiechelon supply chain management system

Table 1. Given values of Supply chain

Echelon	**W**	**D**	**R**
Max inventory level	1400	500	150
Inventory setpoint	320	220	35
Transportation cost(move suppression cost)	P to W 0.5	W to D 1	D to R 1
Inventory weights	1	1	1
Back order weights	-	-	1
Delays	2	3	2

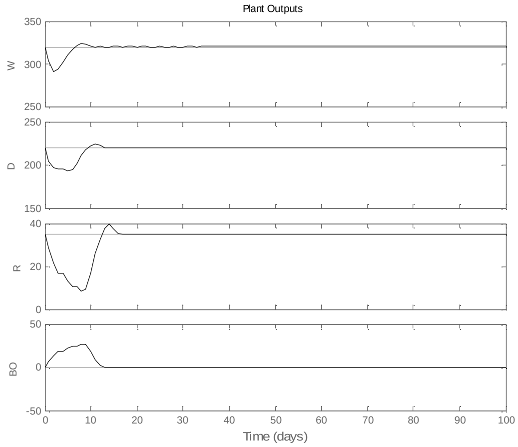

Figure 5. Discrete time dynamic response to a 4 unit constant demand for networks with different transportation delays $L = [2\ 3\ \ 2]$ (first and second method)

A prediction horizon of 25 time periods and a control horizon of 20 time periods were selected and was considered $LO_{i,k} = 0$ for every times. So each delay was replaced by its 4th order Pade approximation (after system model transform to continues time model and then return to discrete time model). In this part, two method of consecutive decentralized receding horizon control that beforehand was stated, applying to large scale supply chain to constant demands equal 4. The simulated scenarios lasted for 70 time periods. As demand is constant, both method have equal response to constant demand that is presented in figure 5 (average inventory levels in each echelon).

The move suppression term would definitely affect control performance leading to a more sluggish dynamic response.

In fact, if suddenly demand changed, the first method can not predict this changes and has not efficiency. Instead second method by online demand prediction in its formulation is efficient. As second method by online demand prediction in its formulation is rather efficient to first method, in this part, second decentralized receding horizon control method applied to the supply chain network with pulsatory variations of customer demand that are seeing in figure 6, once with no move suppression term (Figure 7), and once with move suppression term (Figure 8).

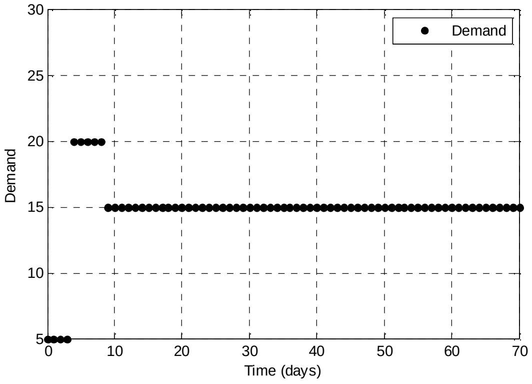

Figure 6. Discrete pulsatory customer demand

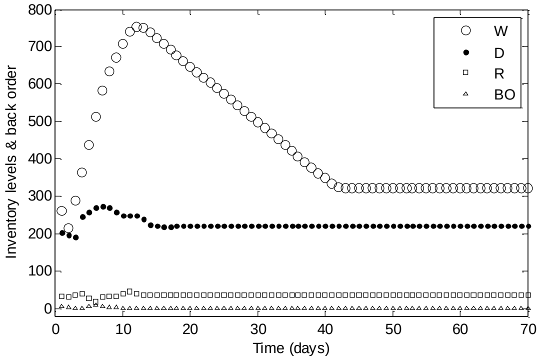

Figure 7. Inventory levels control by second method of consecutive decentralized receding horizon control toward discrete pulsatory demand with without move suppression effect

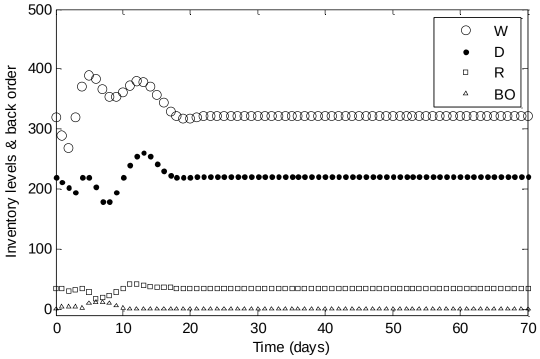

Figure 8. Inventory levels control by second method of consecutive decentralized receding horizon control toward discrete pulsatory demand with move suppression effect

Also second decentralized receding horizon control method applied to the supply chain network with pulsatory variations of customer demand that are seeing in figure 9, once with no move suppression term (Figure 10), and once with move suppression term (Figure 11).

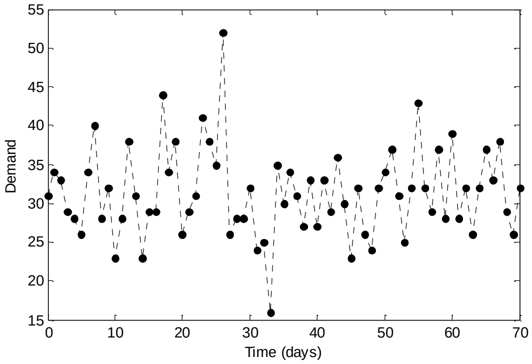

Figure 9. Discrete stochastic demand of gamma distribution

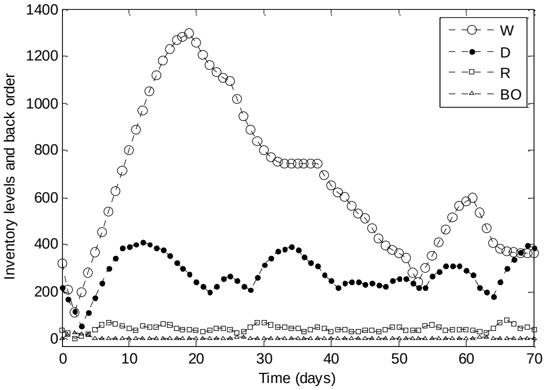

Figure 10. Inventory levels control by second method of consecutive decentralized receding horizon control toward discrete stochastic demand of gamma distribution without move suppression effect

Therefore by using of move suppression, amplitude of variation of outputs will be decreased. So move suppression term increased system robustness toward changes on demands (Figure 11).

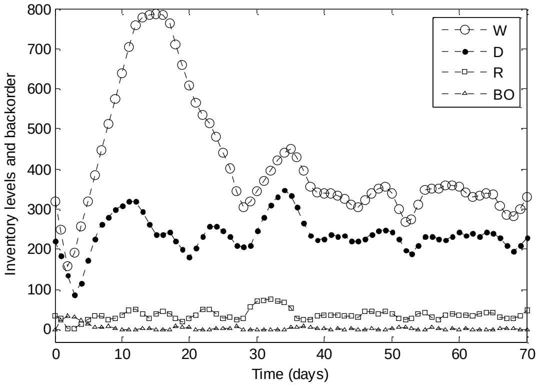

Figure 11. Inventory levels control by second method of consecutive decentralized receding horizon control toward discrete stochastic demand of gamma distribution with move suppression effect

IV. CONCLUSION

Supply chain management system is a network of facilities and distribution entities: suppliers, manufacturers, distributors, retailers. The control system aims at operating the supply chain at the optimal point despite the influence of demand changes. As supply chains can be operated sequentially, locally Consecutive receding horizon controllers applying to a supply chain management system consist of four echelon. Two types of sequential decentralized receding horizon control used. In first method, each node completely by a decentralized receding horizon controller optimized locally for its own policy, and in second method, decentralized receding horizon controllers in each stage are updated in each time period. As second method by online demand prediction in its formulation is rather efficient to first method, in this part, second decentralized receding horizon control method applied to the supply chain network with pulsatory variations of customer demand. Also second decentralized receding horizon control method applied to the supply chain network with pulsatory variations of customer demand. In fact, if suddenly demand changed, the first method can not predict this changes and has not efficiency. Instead second method by online demand prediction in its formulation is efficient. Also a move suppression term add to cost function, that increase system robustness toward changes on demands.

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