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Intelligent Automation In The Project Management of Customer Projects

John M. Aaron

One of the most important applications of modern data science tools and techniques is to manage business process performance in a more effective and efficient manner. Six Sigma practitioners have historically used control charts and other statistical tools for this purpose. In a complementary way, control engineers have traditionally used mathematical techniques to embed controllers such as PIDs and MPCs to keep the performance of dynamic systems such as aircraft, automobile cruise controls, etc. on track. Now with the availability of modern machine learning, reinforcement learning and higher speed processing, the tools and techniques from both data science and control engineering can be combined by management practitioners to take business process improvement and control to a higher level of accuracy and performance. The purpose of this paper is to demonstrate how this can be accomplished using a very simple example of a *project-oriented* business process producing consistently on-time deliveries of products or services to customers.

Our Example—Situation Analysis

Our example begins as a story. Let's assume the role of a naval ship captain in the 17th century. His mission is to leave the south port of the British Isles, sail the eastern coast of the island and deliver supplies to a customer at the northern port in no later than 6 days. The captain, who assumes the role of a project manager, plans to sail 8 hours each day and to make evening rest stops on land along the way. Assuming good weather throughout he plans the full trip to be 430 miles and expects an average travel speed of 8 knots. Figure 1 below illustrates the captain's plan as the dark dotted line.

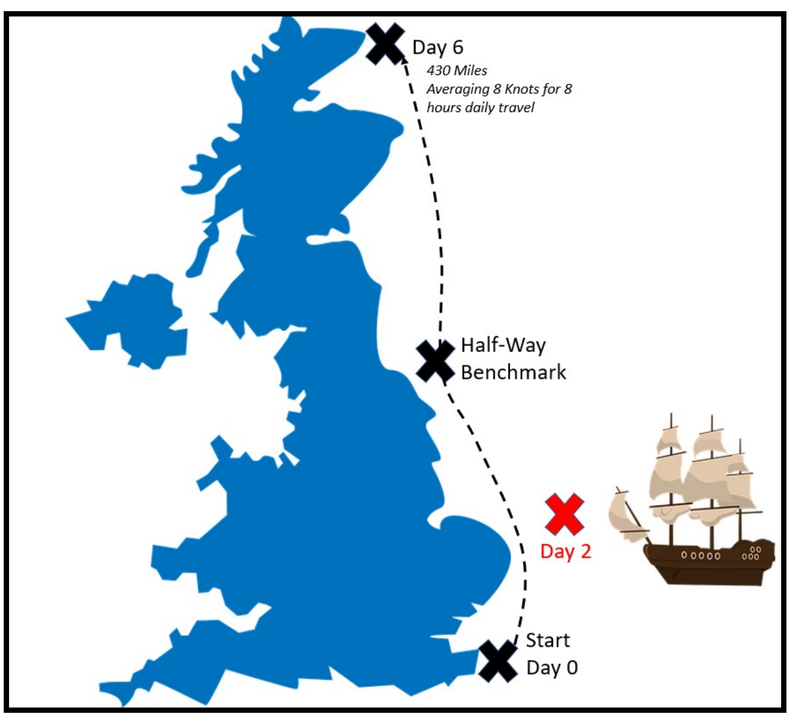


Figure 1

The Captain takes on the role of a project manager.

Note: Powerpoint available from author: john.aaron@milestoneplanning.net

The voyage begins as planned, and all appears well through day 1. On day 2, however, the ship sails into bad weather. As the captain compares his actual sailing progress with visual benchmarks on the island coast, he notices that the ship is falling behind plan. The wind and waves have reduced the ship's average speed to 2 knots indicating that the ship will not reach the half-way benchmark until day 6. Because the delivery of goods to the final northern port by day 6 is time-critical, the captain decides that the ship must accelerate to get back on plan and then maintain an appropriate velocity in order to arrive at the northern port on time. The captain assesses the weather situation, and decides that the lack of proper wind requires that the ship's crew must row the ship throughout each daily shift for the remainder of the journey.

The captain assigns 20 of his strongest crew members to become rowers. He sets a rowing rate based upon his personal experience and his best guessing of the velocity that will be needed to get back on schedule. The captain's recovery plan calls for the ship to travel at "cruise" speed at an average rate of 8 knots throughout each daily eight hour shift . The captain wants to maintain only the required rate, but not faster, so that the rowing crew does not become overly tired.

To help keep the crew rowing at the appropriate pace, the captain orders the ship's drummer to begin beating the drum for "cruise" speed which should result in an average speed of 8 knots. Following the recurring beat of the drum, the crew synchronizes their rowing rate to the pace of the experienced drummer's beat. In the event that maintaining "cruise" speed becomes inadequate to get the ship back on schedule, the captain's contingency plan calls for the crew to row at " attack" speed at short intervals which is at an even faster rate of 12 knots. The captain will monitor performance closely.

The captain's plans are very imprecise given the capabilities available during the 17th century. Given the captain's experience along with some luck, the ship may or may not make it to the northern port on time by day 6. But regardless of outcome the captain has performed a valuable project management role of planning, monitoring and controlling this process.

Adding Technology To Our Re-Planning Example

For part 2 of our example we now imagine employing a time machine that enables the ship's captain to be gifted with a modern day computer along with state-of-the-art statistical software, mathematical control techniques and sensing devices. How might the captain take advantage of these capabilities to reduce the schedule risk of the journey and to optimize overall performance of the rowing crew?

To demonstrate how the captain might better accomplish his goals and reduce risk using this technology, the captain could build some data science and process control planning models in MATLAB/Simulink . He could then deploy those models into the ship's hardware and then control the process throughout the execution of the journey.

As a first planning step the captain will use these tools to better determine how the appropriate speed will be attained by the rowing crew and how the speed will be consistently maintained. The captain uses Newton's second law, the governing equation for the system becomes:

$$m\dot{v} = u - bv$$

Where :

m=mass of the ship in kilograms

b= an air drag coefficient that is proportional to the velocity (v) of the ship

u=the force generated at the interface between the ocean and the hull of the ship caused by the controlled rowing as measured in Newtons

$\dot{v}$ =acceleration (the derivative of velocity with respect to time) $\frac{dv}{dt}$

$$\int \frac{dv}{dt} dt = v$$

The captain models the system by summing the forces on the mass and integrating the acceleration to give the velocity. Using Simulink the captain models the integral of acceleration as shown below in Figure 2:

The captain experiments. By applying a simulated step force pulse measured in Newtons as the input to the Simulink model, the captain identifies the expected ramp up and steady state velocity from the force created by rowing. By understanding the relationship between force, acceleration and velocity, the captain can more accurately estimate the required crew size of rowers needed to achieve the required rate of 8 knots. Further, he can quickly re-estimate any crew size adjustments needed if the planned rate does not immediately produce the desired performance improvements.

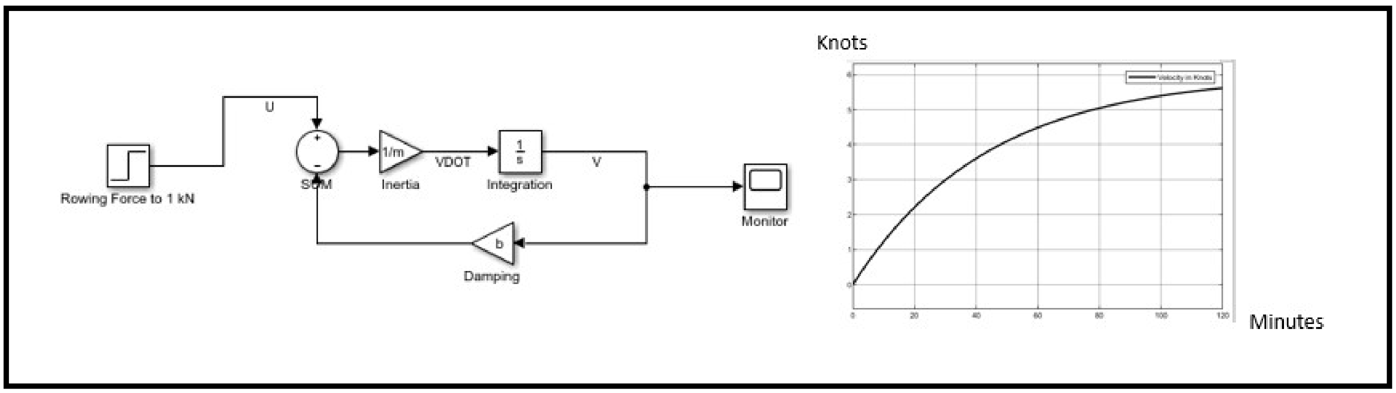


Figure 2 (A frequently cited example of equations of motion)

As a next planning step the captain wishes to ensure the accuracy of the drummer 's pace so that the drummer keeps the proper number of beats per minute to trigger the rowers to maintain the proper pace without becoming overly tired. To accomplish this the captain uses Simulink to construct an equation model for a converter that transforms drum beats per minute to the precise force dimension as measured in Newtons. And then the proper force signal is converted to velocity using the model identified in Figure 2 above. By connecting the two models and running the simulation, the captain discovers that the drummer should maintain a cadence of 12 beats per minute in order to produce the required eight (8) knots of speed that will be needed on average. Figure 3 illustrates the connection of the two models in Simulink. The captain then decides that a modern drum machine would yield greater precision than a human drummer.

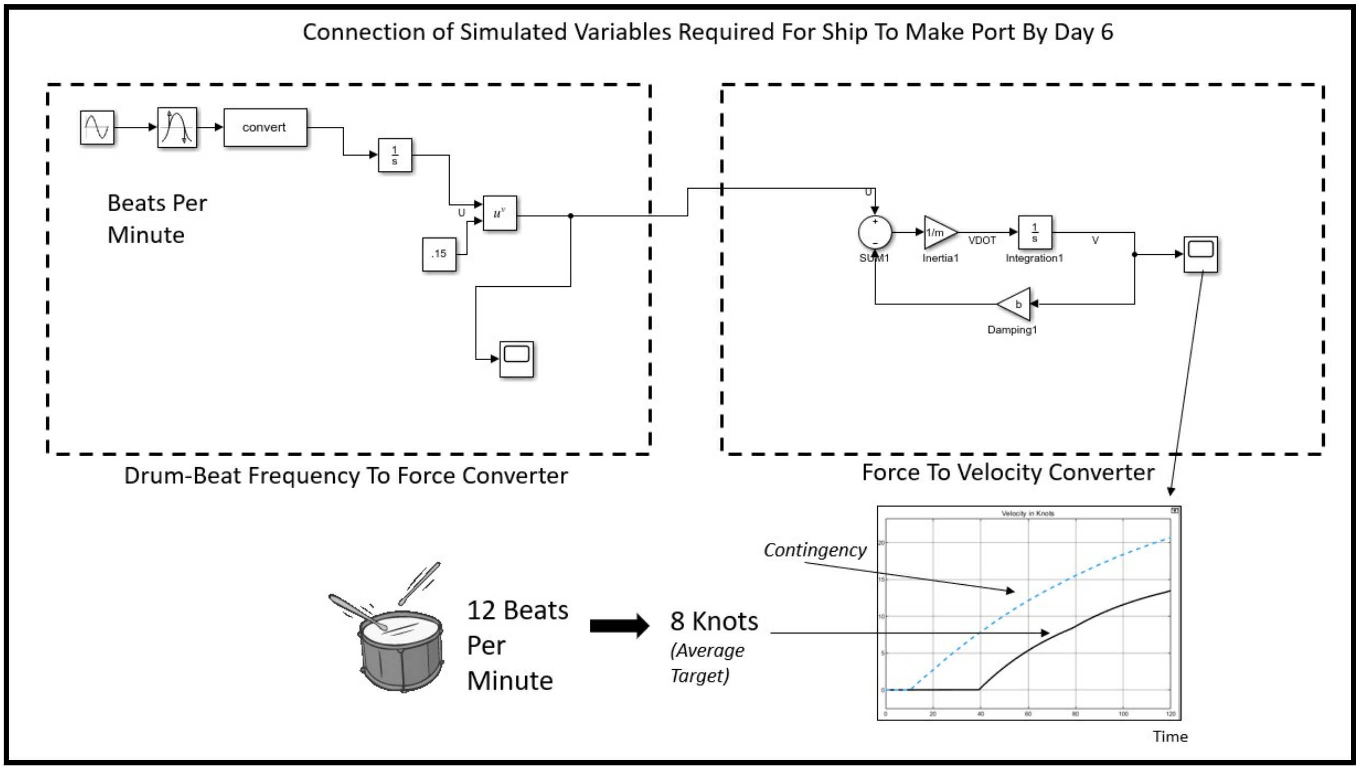
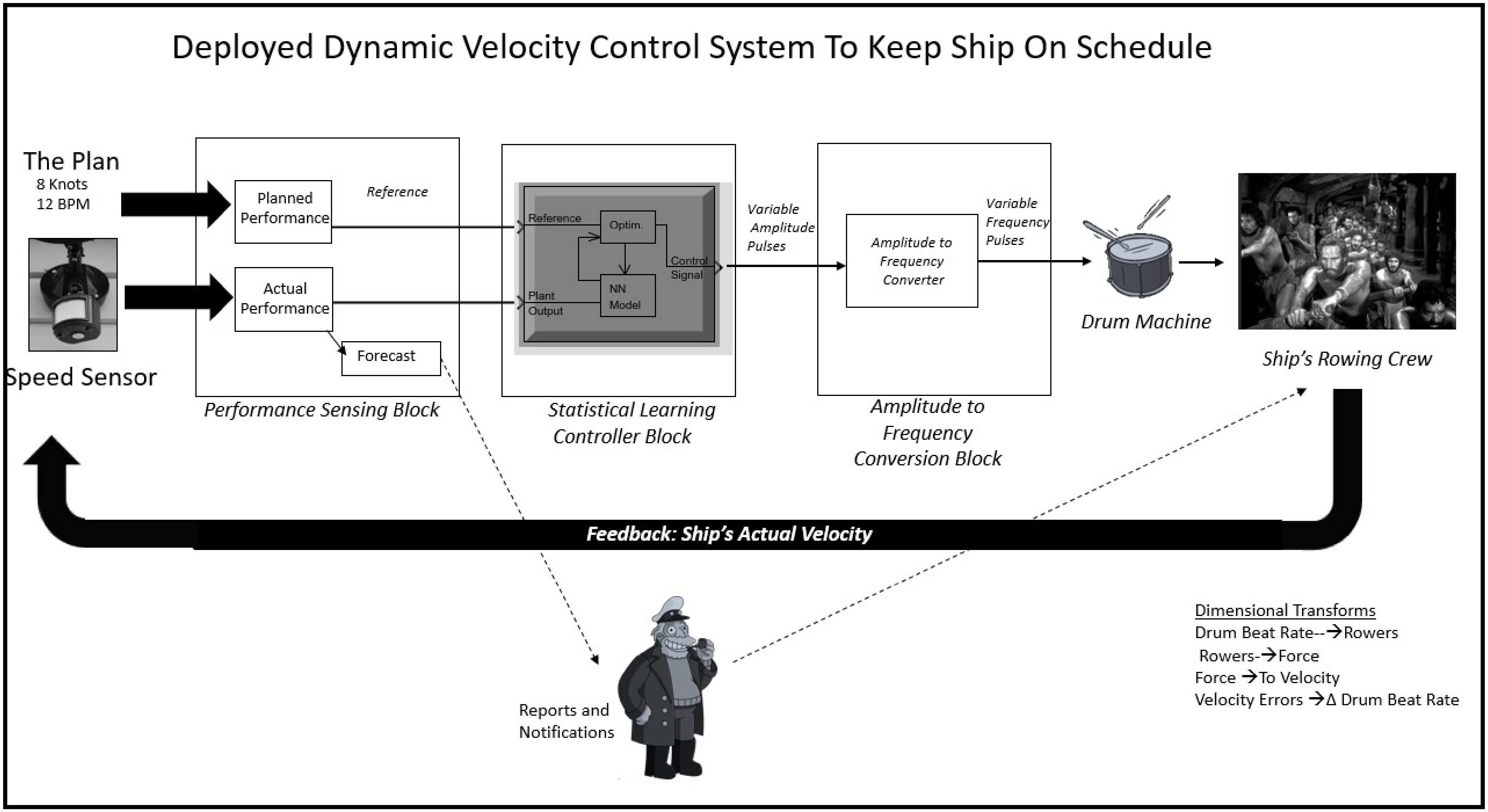


Figure 3

Testing, Deploying and Operating the Basic Velocity Control System

With the planning and system design completed, the captain is now ready to finish building, testing and deploying the basic control system hardware and software on the ship. Refer to Figure 4 on the following page. The system contains a speed sensor that sends actual velocity information to a controller that compares actual versus planned performance of the ship. The controller also provides forecast reporting to the captain and crew. The controller uses any differences in performance between actual and planned (errors) to generate a control signal that is sent to a drum machine by way of a frequency converter. The drum machine begins operation at the baseline 12 beats per minute that paces the rowing crew to deliver an average velocity at the targeted 8 knots. During the journey if weather and tide conditions change favorably or unfavorably the speed sensor will pick up deviations from plan and send signal changes (up or down) through the system leading to appropriate adjustments in the drum rate which, in turn, drive velocity corrections through the resulting changes in the rowers' pace. On the human side of the equation, the captain closely monitors the system performance and keeps the crew fully informed and motivated.

By employing this control technology the captain is much more likely to successfully achieve his mission with an on -time arrival at the northern port on day 6.



Deployed Dynamic Velocity Control System To Keep Ship On Schedule
The Plan
8 Knots
12 BPM
Speed Sensor
Planned Performance
Reference
Actual Performance
Forecast
Performance Sensing Block
Reference
Optim.
Plant Output
NN Model
Control Signal
Statistical Learning Controller Block
Variable Amplitude Pulses
Amplitude to Frequency Converter
Variable Frequency Pulses
Amplitude to Frequency Conversion Block
Drum Machine
Ship's Rowing Crew
Feedback: Ship's Actual Velocity
Reports and Notifications
Dimensional Transforms
Drum Beat Rate--→Rowers
Rowers-→Force
Force →To Velocity
Velocity Errors →Δ Drum Beat Rate

Figure 4

Implications to Business Process Managers and Project Managers

The process described in this example uses a proven, established set of control tools that have been employed by control engineers for years. Yet, today we still find that current-generation business process managers continue to rely upon the manual kinds of steps that our 17th century sea captain originally employed. By allowing technology to perform the tracking and control steps instead of doing it manually, the captain had more time to spend on more strategic issues requiring his attention as well as on team communication. Today's business process managers will likely gain similar benefits by adopting these kinds of automated tools.

Control engineers traditionally use PID and MPC controllers in their designs. These kinds of controllers can take a long time to tune properly. So, it is worthwhile to consider other kinds of controllers that can use data science techniques to tune automatically. In our example (Figure 4) we went beyond PID and MPC approaches and used a more modern neural net controller that relied upon machine learning to become automatically trained and accurately tuned. And it is possible to go even further, there is now another generation of controllers that uses *reinforcement learning* to become accurately tuned even more quickly and providing even greater accuracy. We will discuss reinforcement learning controllers in the next section below.

The Intelligent Business Process: Combining Feedback and Feedforward

Figure 5 on the following page provides a high level block diagram of the Reinforcement Learning (RL) version of the control system that could be used by the captain in our ship example. By using RL the captain reduces the tuning time of the controller, and he attain greater precision. The system contains sensors, modular blocks flowing left to right and a control loop .

Much like the control system shown on Figure 4, the RL control system illustrated in Figure 5 contains a velocity feedback control signal by way of actions from the Agent block back to the Plant block which trigger appropriate adjustments in the drum rate. RL creates a triplet where Monte Carlo methods generate random actions that are compared with Rewards as well as with the various "State" observations (such as Day Number on the journey). The RL system uses iterative statistical learning methods to arrive at optimal actions given the various state observations and rewards coming from the Reward block. Hence, RL allows the practitioner to optimize by considering multiple secondary input variables—not just the primary variable , velocity. This combined capability of feedback and feedforward enables the control system to anticipate changes in the target variable (velocity). As a result the system takes preventative control actions as well as corrective control actions given the input from multiple sensor types.

To consider the benefits of combining feedforward and feedback control capabilities, let's assume for our ship example that the weather is normally bad on Day #2 of the journey. After experiencing a number of recurring journeys, the RL system learns to compensate on Days 1, 3, 4, 5 and 6 for the anticipated problems that typically occur on Day 2. Figure 6 on page 8 plots actual velocity (in Miles Per Minute) actual versus planned. Notice how RL compensates for the *recurring* difficulties encountered on Day#2. The result of this compensation can be seen as on-time performance throughout the entire journey as illustrated on Figure 7.

In addition to greater accuracy one of the most important benefits of RL controllers is their relatively easy adoption by data scientists and business process managers. Historically, controller design requires extensive

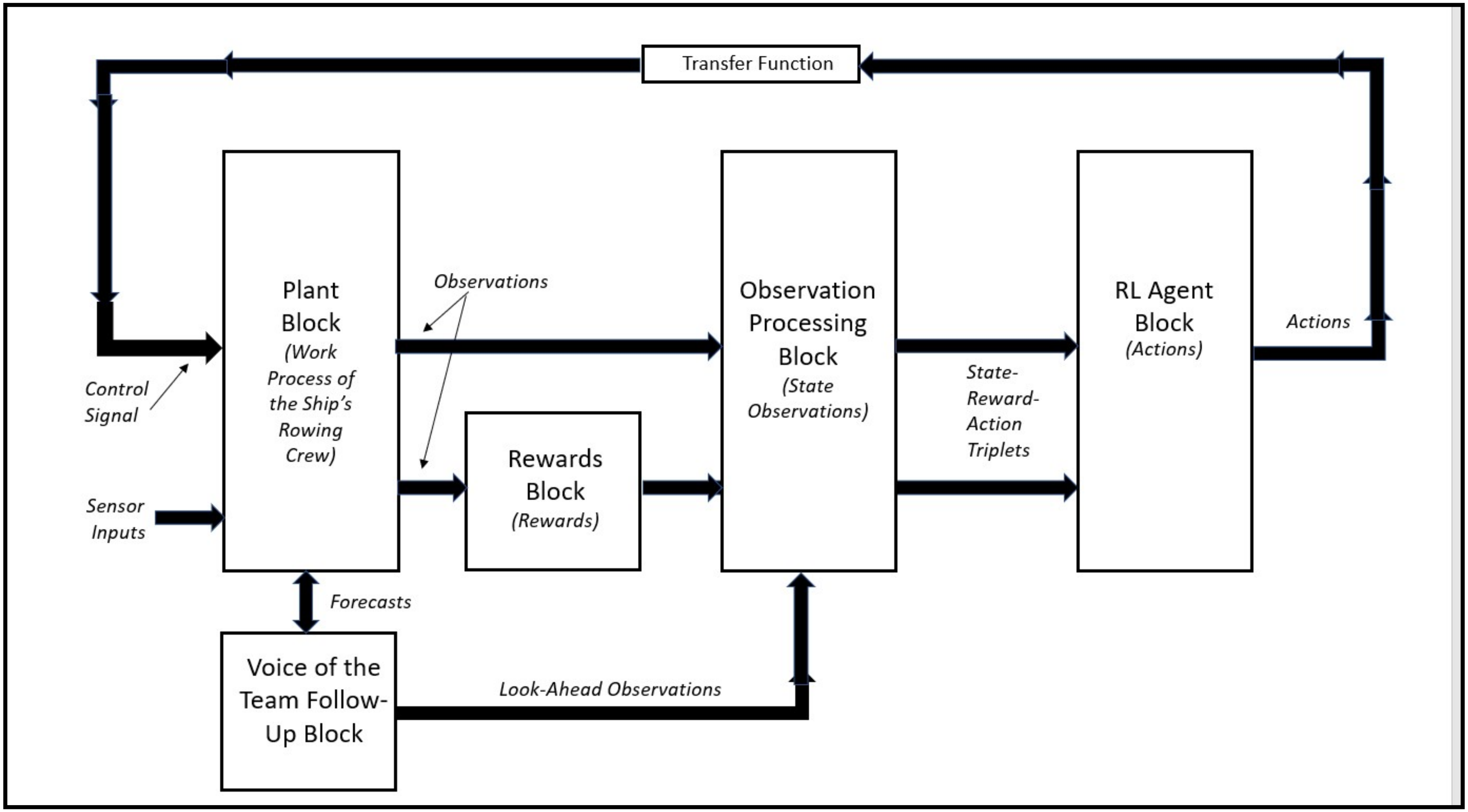


Figure 5

RL System

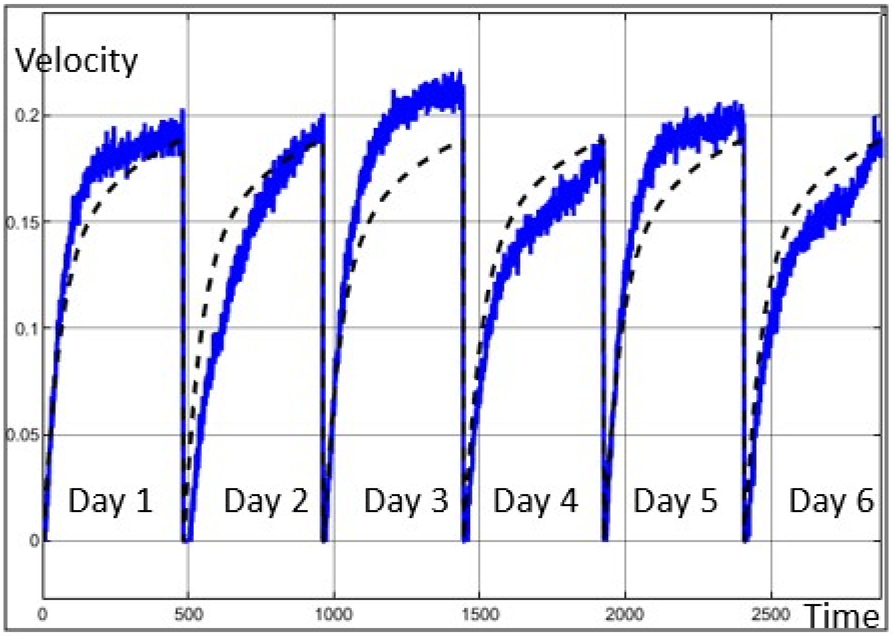


Figure 6 —Velocity Vs Time (Solid=Actual, Dashed=Planned)

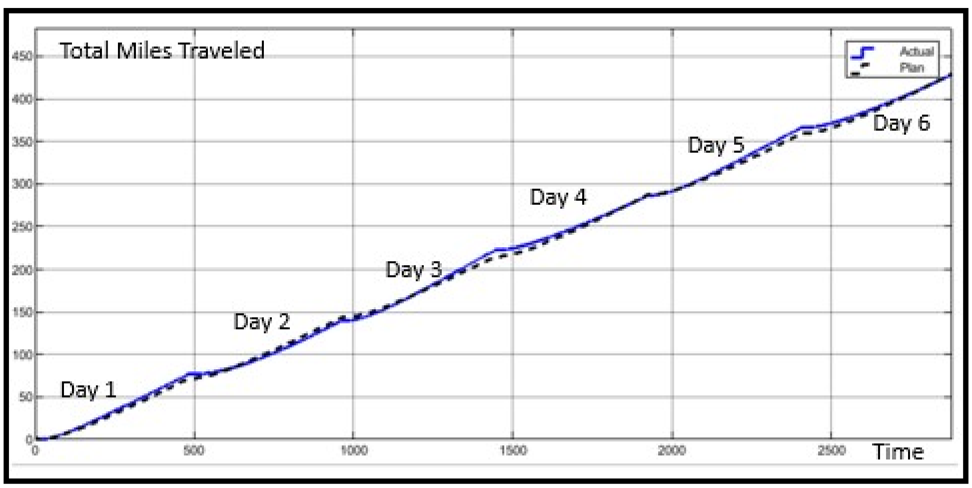


Figure 7 —Miles Traveled Vs Time (Solid=Actual, Dashed=Planned)

tuning and system domain knowledge. RL removes these tedious requirements which make it a useful general planning and control tool for business process management and improvement. No longer is the business process practitioner limited to using only the equations governing the *physical sciences* that has been the traditional purview of engineering. Now, given RL technology the equations of business, finance, economics and the social sciences can be added into the business process management improvement toolset available to six sigma and project management practitioners.

The parallels between our automated ship example and automated project management are striking. Although application of Newton's second law is usually intended for the physical sciences, there can be direct transference to day-to-day project management. For example, Newton's parameter mass (m) is analogous to project scope. Velocity (v) is analogous to rate of project activity completion. The drag coefficient (b) is analogous to emergent project issues. And finally the force (u) is analogous to the summation of project resource effort applied to the project. It is remarkable how closely the velocity curve shown in figure 2 resembles the output of the neoclassical economic production function where output is a function of labor and capital. We find that many of the same rules governing the physical sciences can be applied to business, finance and the social sciences. This creates many value added modeling opportunities for the practitioner.

Adding Voice of the Team (VoT): Combining Human and Machine Predictive Intelligence

In the ship example we demonstrated how process signals can be combined using feedback and feedforward control methods for the purpose of optimizing process performance. Feedback and feedforward methods perform predictions using a variety of relevant sensor inputs. Their effectiveness relies entirely upon recognition of *recurring* patterns extracted from the time series signals of the ship's hardware. In a sense these signals reflect a Voice of the System (VoS). But what if the captain and crew had their own valid insights that were idiosyncratic and *non-recurring*. How might we include these unique insights into our model in order to make an even more powerful predictive model? To accomplish this we rely upon a Voice of the Team (VoT) survey that probes the team member's beliefs about emerging problems.

Referring back to Figure 5 we see a block titled "Voice of the Team Follow-Up". The purpose of this block is to transform recurring VoT survey data that measures look-ahead information from the captain and crew (team) members and converts that information into *forecasts* that help drive the statistical learning of the controller. The feedback and feedforward control signals combine machine intelligence with human judgment. The machine extracts and recognizes recurring patterns; the VoT identifies idiosyncratic turning points that would be noticed by the experience of the team yet likely be missed by the machine. Ideally we create an optimized system that combines the best of both man and machine.

Applying Risk Management to the Transformation Methodology

Thus far in this simple case study we have focused upon the technical details of an automated project planning and control system. The question arises should the captain actually go forward with this automation project? From a benefits versus costs perspective it might appear straight forward that the captain should go ahead and install the automated system on his ship. But might there be some negative potential consequences that he did not anticipate? To assess these risks the captain adopts a transformation methodology as illustrated in Figure 8 on the following page.

Figure 8 describes a rather old but effective transformation methodology adopted from Dietrich Dorner's 1989 book *The Logic of Failure*. Dorner's key point was that regardless of a decision maker's good intensions, failure frequently occurs in change efforts when the decision maker does not think through the downstream consequences of his actions. Dorner found that successful change becomes more likely when the decision maker adopts the five step approach described in Figure 8.

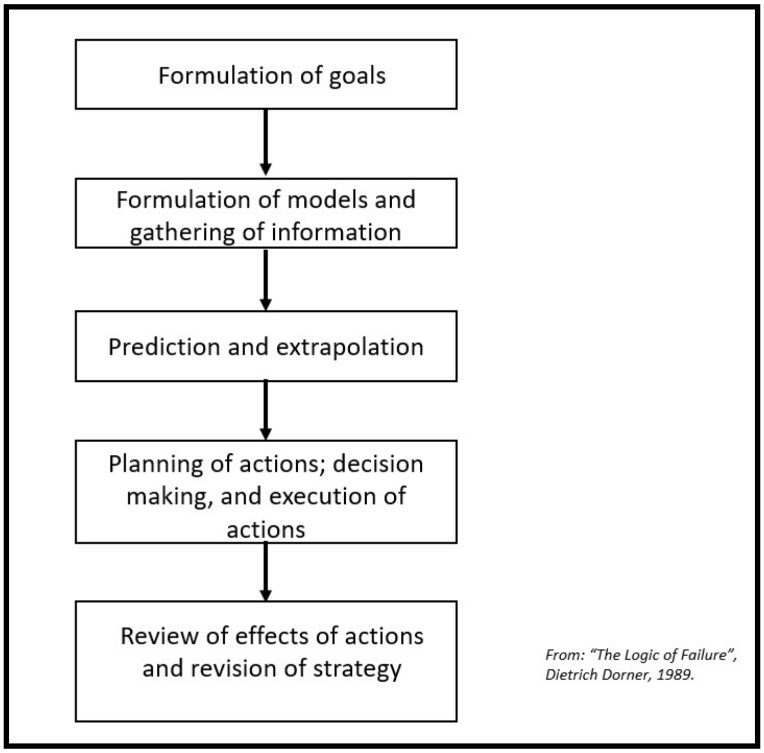


Figure 8 —Dorner's Transformation Methodology

Throughout this paper we have already described the first two steps of the methodology (i.e. formulation of goals, models and gathering of information). We have also adequately covered the last two steps. Dorner's third step, prediction and extrapolation, requires recursive system modeling and is worth adding to our ship example. Refer to Figure 9.

Figure 9 illustrates a recursive system model as applied to the ship case study using a mind map. Performing this kind of risk planning exercise will help the captain identify any unforeseen down stream consequences.

The path in black identifies the expected positive consequences of installing the new equipment on the ship. The captain would benefit (+) by increasing his on-time arrival rate which would increase his revenue and ultimately increase demand by the customer for future deliveries. This is the intended result of the project.

The paths in red, however, illustrate hypothetically the potential unforeseen negative consequences of installing the new equipment aboard the ship. First, with the new approach, the rowing crew will require more food to eat to sustain their increased energy levels. This will increase the ship's operating costs which will have to be passed on to the customer, and this could decrease demand for future deliveries. Similarly, the crew might notice that the captain has increased revenue from the improved on-time delivery rate, and as a consequence they may demand higher wages. Higher wages would increase the ship's operating costs which would have to be passed on to the customer. This would likely create a downward demand pressure or price concessions by the captain for future deliveries.

By using a recursive planning model as described above, the captain would likely make a better decision regarding going forward with the equipment project. This is a risk planning skill that can be applied to any business transformation initiative.

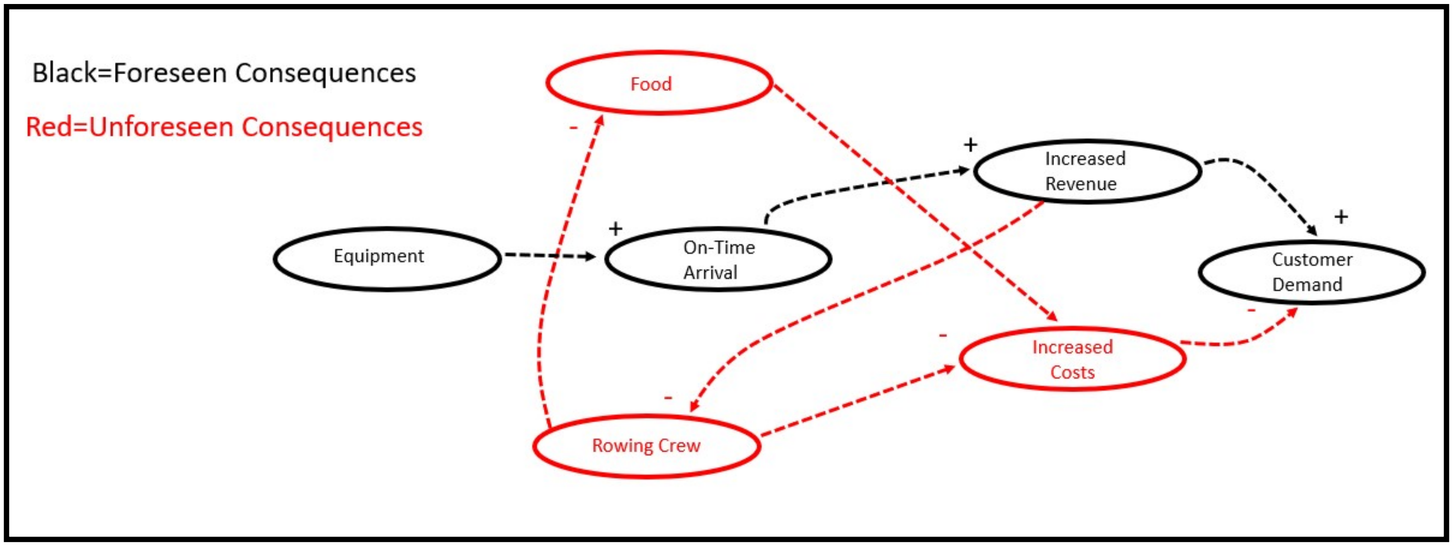


Figure 9 —A Recursive Planning Model For the Ship Example

Transforming Modern-Day Project Management Processes Using Auto VoS and VoT

The ship example takes us backward in time to an era when achieving project schedule adherence was a simpler intellectual challenge for the project manager. The manager had to ensure that adequate effort was being applied by the workers over a sufficient time period. The proper pace of the drum along with physical rewards and punishments were the tools available at that time. Project environments today are more complex, however, and managerial tools need to be more sophisticated to accommodate this complexity.

Workers still need to hear the proper pace of a drum to drive the velocity requirements of the project. And the drum rate needs to quickly respond to actual performance shortfalls. A good VoS system will provide this feedback using feedback analytics. But workers also need the look-ahead capability of predictive controllers that are driven by VoT and feedforward VoS. Perhaps the time is now right to take the concept of auto project management more seriously. We will address this topic rigorously in the companion slide deck.